HOUSING SPECULATION, GSES, AND CREDIT MARKET SPILLOVERS

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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 supply to speculative investors in housing, leading to higher interest rates and reduced lending. Bank and non-bank lenders responded similarly, suggesting that deposits do not offer banks a comparative advantage in mortgage lending. Lenders adjust to the policy not only at the portfolio level but also by reallocating mortgage credit across their local markets. The results suggest that lenders manage credit provision not only in a macro sense – the focus of most research – but also market-by-market.

1. INTRODUCTION

Housing prices rose faster during the period surrounding the COVID-19 pandemic than even in the run-up before the 2008 Global Financial Crisis.[1] This boom coincided with a rapid expansion of loans purchased by the Government Sponsored Enterprises (GSEs).[2] During the early quarters of the pandemic, speculative transactions also rose sharply (Figure 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 house transactions compounded the rising risk exposure at the GSEs.[3] 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. Detailed data on mortgage originations allow us to show that lenders comply with the constraints not only at the portfolio level, but also by reallocating across local markets. In addition, we show that the policy spills over to other local credit markets.

At the end of the Trump Administration, the U.S. Treasury – the residual claimant in the GSEs – initiated a policy to strengthen the GSEs' capital ratios and reduce their risk, with the ultimate aim of moving them out of government conservatorship and back into private hands.[4] The policy was implemented by amending the Preferred Stock Purchase Agreement (PSPA), which we describe in detail below. The amendment capped the GSEs' ability to invest in both risky loans (limiting exposure to low FICO-score borrowers, to high loan-to-value loans, and to

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[1] According to the Case-Shiller national index, housing prices rose about 40% in the three years before the peak in mid-2006. In contrast, prices rose 45% between mid-2019 and mid-2022 (see: https://fred.stlouisfed.org/series/CSUSHPISA).

[2] See the GSEs' annual reports at https://www.fanniemae.com/media/document/pdf/q42021.pdf and https://www.freddiemac.com/investors/financials/pdf/10k_021022.pdf.

[3] See https://www.cnbc.com/2021/01/22/existing-home-sales-in-2020-were-highest-since-in-over-a-decade.html

[4] 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.

high debt-to-income borrowers) and loans for housing speculation (defined as mortgages for either second or investment homes). We study the impact of these changes on credit supply, housing transactions and local real economic 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 lenders when they exit these segments.[5] We also find important second-order effects, as the changes in GSE policies spill over into the local small business lending markets.

We first focus on the conforming mortgage markets, where the GSEs are active, to test whether the policy change worked as intended. In the analysis, we separate the conforming market into three non-overlapping segments: 1) speculative mortgages; 2) risky but non-speculative mortgages; 3) safe, non-speculative mortgages. The first two segments were potentially affected by the policy. In some of our tests, we also sub-divide the speculative mortgages into second-home and investment home mortgages.

Compared to safe mortgages, lenders reduce speculative-mortgage sales to the GSEs during the period of policy implementation, but the policy has little impact on sales of non-speculative risky mortgages. This non-result squares with existing evidence (which we verify) that the limits on risky mortgage purchases in the PSPA were rarely binding prior to the pandemic (Golding et al., 2021); hence, this part of the policy had little bite. 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.

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[5] 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 10 and 11) where we only include banks in the sample when we study the interaction between the purchase cap policy and the presence of bank branches.

Despite this large overall drop, we show that within the sample of speculative mortgages, lenders skew their sales toward ex-ante riskier ones after the policy caps go into effect. This adjustment partially offsets the larger aim of the policy change, which is to lower the risk-exposure of the GSEs. Based on our regression analysis, mortgages to borrowers with a FICO score that is one standard deviation below average are about 0.8 percentage point more likely to be sold after the policy, and mortgages with CLTV that is one standard above average are more than 3.8 percentage points more likely to be sold.

We then show that the price of credit – mortgage interest rates – increases by about 10 basis points for speculative loans relative to safe loans, consistent with a decline in supply from the policy. In contrast, risky mortgages, where the policy had little effect on GSE sales, do not experience an increase in rates during the period of policy implementation. We decompose these effects based on lender type (banks v. non-banks) and by the type of speculative mortgage (second-home v. investment-home mortgage). Both types of speculative mortgages respond similarly, meaning large declines in the likelihood of sale to the GSEs and increases in interest rates. The policy's effect on non-bank sales to GSEs exceeded that of banks, who are better able to substitute financing from GSEs with their substantial balance sheet capacity, as deposits grew sharply during the policy period. We find, however, that non-banks increase private securitization much more than banks, while interest rates on mortgages originated by non-banks adjust similarly to that of bank-originated mortgages.

Next, we explore how lenders adjust the quantity of credit supplied when the GSEs reduce their purchase activities. We find very large adjustments across multiple margins, which implies an important subsidy has been removed by the policy. First, credit origination by lenders constrained by the caps declines by about 18% in the affected segment. Lenders more exposed to

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the policy – based on pre-policy percentage of affected mortgages sold to the GSEs – experience relative declines in both speculative mortgage originations and mortgage applications, and the decline has a similar magnitude for both second and investment home mortgages. Since the decline in originations is similar in magnitude for applications, the effects on quantity are happening because lenders discourage some borrowers from applying, or simply stop serving the market (as opposed to adjusting acceptance rates). Consistent with a causal effect of the policy, lenders do not adjust the quantity of either safe or risky mortgages.

Importantly, we find *no* difference in the supply response of banks v. non-banks. Both lender types change prices and quantities in response to the policy with similar magnitude. The similar decline, on its face, seems surprising because banks can replace GSE sales either by funding lending on balance sheet (with deposits) or by increasing their sales to non-GSEs, whereas non-banks have only the latter source of substitute financing. Our results imply that deposit-financing does not offer banks a comparative advantage in mortgage lending in the presence of an active, private securitization option for non-banks. This result helps explain the dramatic increase in market share of non-bank mortgage lenders over the past three decades (Buchak, et al., 2024).

Second, we test for local effects, both direct (effects on the speculative segment) and indirect (effects on the market for small business loans). For these tests we construct a three-way panel dataset at the lender-county-time level, which allows us to test how the allocation of mortgages *across* each banks' markets changes in response to the policy. By absorbing lender-quarter fixed effects, we remove all lender heterogeneity and thus focus solely on how different levels of pre-policy exposure change origination behavior. We show that lenders which have sold more speculative loans from a given county to the GSEs before the policy reallocate their originations away from those areas (relative to other areas served by that lender). Since this

analysis controls for lender-time effects, the results imply that they manage credit not only at the portfolio level but also market-by-market.

Third, we find evidence of local credit spillovers to the market for small business (bank) lending. 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. The spillover suggests a synergy at the local level, as banks which reduce lending in speculative mortgage markets may lose information about the local market. Moreover, borrowers in the affected markets may experience a negative housing wealth effect from the decline in credit supply (Schmalz, et. al., 2017). Hence, a decline in speculative lending leads to less lending to local businesses.

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 limited liability companies (LLC) and 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 residence (non-speculative) market increase with treatment exposure, consistent with less competition in the housing market given less credit flowing to the speculative home buyers. Despite these adjustments, we find that house-price growth slows in markets more exposed to the policy caps (consistent with a negative wealth effect). We also test for, but do not find, declines in the construction sector in more affected areas. Because the policy was only in effect for less than one full year, its impact on investment/real outcomes may have been attenuated.

Our paper contributes to three strands of 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 (Brueckner, Kahn, and Lin, 2021; Howard, Liebersohn, and Ozimek, 2023; Davis, Ghent, and Gregory, 2024). 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 mortgage-backed securities (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 jumbo/non-jumbo spread differential, which has exhibited substantial variation over time (DeFusco and Paciorek, 2017; Alexandrov, Conkling, and Koulayev, 2022; Adelino, Schoar, and Severino, 2024). 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 these high-risk mortgages and private-label mortgage-backed securities (Wallison and Calomiris, 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. Several papers (Jeske, Krueger, and Mitman, 2013; Elenev, Landvoigt, and Van Nieuwerburgh, 2016; Gete and Zecchetto, 2018) apply general equilibrium models to study the impact of GSE subsidies on credit supply and examine the distributional implications if these subsidies were removed. McKenzie (2002) and Richardson, Van Nieuwerburgh, and White (2017) provide survey of this literature. Our paper provides the most direct evidence that GSE subsidies affect mortgage credit supply, and also that lenders 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 (Fu, Qian, and Yeung, 2016; Agarwal, Badarinza, and Qian, 2018; Deng et al., 2019; Chi, LaPoint, and Lin, 2020; Agarwal et al., 2021; Deng et al., 2022;). 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 (Nathanson and Zwick, 2018; DeFusco, Nathanson and Zwick, 2022), as well as their role in

mispricing (Chinco and Mayer, 2016) and potentially destabilizing housing markets (Gao, Sockin and Xiong, 2020; Garcia, 2022; Mian and Sufi, 2022).

2. SETTING

The Preferred Stock Purchase Agreement (PSPA) was created when Fannie Mae and Freddie Mac were taken into government conservatorship during the 2008 Global 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 risky home purchase single-family mortgage loans to 6% and risky refinance mortgages to 3% of single-family mortgage acquisitions, based on a trailing 52-week period. Risky 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 or investment homes (which we will refer to as "speculative mortgages") to 7% of single-family mortgage acquisitions over the preceding 52-week period. [6]

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

The Purchase Cap policy was announced on January 14, 2021 and went into effect on April 1, 2021, but was suspended in September 2021.[7] We confirmed with GSE insiders that the purchase cap is implemented on a lender-by-lender basis. In January of 2022, the FHFA announced that higher gaurantee 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.[8]

Given this history, we focus on the five quarters which surround the initial amendment to the PSPA, running from Q3, 2020 to Q3, 2021. The 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 implementation/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 risky mortgages – both for purchase and refinance – consistently remained well below the limit imposed by the policy (6% for purchase mortgages and 3% for refinance). As

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[7] See https://singlefamily.fanniemae.com/media/25286/display and https://www.fhfa.gov/news/news-release/fhfa-and-treasury-suspending-certain-portions-of-the-2021-preferred-stock-purchase-agreements.
See https://www.fhfa.gov/sites/default/files/2024-05/GFee-Report-2022.pdf

we will show, the policy likely had large effects on credit in the speculative market but limited effects on non-speculative risky mortgages. We thus begin our formal empirical tests comparing the effect of both policies on credit supply. In later tests, when we consider second-order effects, we focus only on the speculative markets.

Figure 2, Panel B reports the fraction of speculative and risky 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 percent, in relative terms, 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. Despite the large decline in sales of speculative mortgages to the GSEs, the fraction of speculative mortgages held by originating lenders increases sharply (Panel C). 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 lender level, the lender-market level, and the 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 and interest rates. Second, we aggregate to the lender 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 lender-county-time level to test for local effects; this empirical strategy allows us to fully remove both lender-time and county-time effects, thus zooming in on the reallocation of credit across markets. Fourth, we consider how the policy's effect on credit supply affects housing markets and local economies, with data measured at 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, among other things, 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 and LLCs.[9] We use the CRA lending data from the FFIEC 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.

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[9] 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.

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 lender-year-quarter level; Panel 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

For the loan-level analysis, we follow several papers in the mortgage lending literature (Bhutta et al., 2020; Bhutta et al., 2021; Bartlett et al., 2022; Amornsiripanitch, 2023) and construct our sample from first-lien home purchase and refinance, single-family, 30-year fixed-rate conventional conforming mortgages. 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 as being ineligible for GSE purchase.[10] 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 between 2020Q3 and 2021Q3, inclusive. The filters leave us with approximately 6.8 million mortgages.[11]

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

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[10] 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.
[11] The special feature filters dropped approximately 10% of all conforming conventional 30-year fixed rate mortgages.

(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:

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

where i refers to loan, j refers to lender, k refers to census tract, and t refers to year-quarter. Equation (1) looks on its face like a panel regression, but it is not. We are not following the same loan over time. But we still need to control for local heterogeneity and lender-specific time trends, which we do with δ_k and $\gamma_{j,t}$ (fixed effects). These effects absorb the direct effect of both *Announcement* and *Implementation*.

The dependent variable in Equation (1) is an indicator set to 100 for originated mortgages sold to Fannie Mae or Freddie Mac by the end of the 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. For GSE sales, 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 or lender-year-quarter fixed effects. Control (i.e., safe) mortgage mortgages are those associated with conforming mortgages 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: an indicator for refinancings, 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.

Recall that Figure 2 suggests that the Purchase Caps bind for speculative mortgages but not risky mortgages. Table 2 supports this claim, after absorbing the 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 safe 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 about 23 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 66%.

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 small and mostly insignificant. Consistent with the aggregate trends, which show that the fractions of risky purchase loans and refinance mortgages are below the caps before the policy, the policy does not significantly affect the probability of risky 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 divided by 100 (FICO); 2) CLTV ratio; and 3) DTI ratio. Two of these interact significantly with the post-implementation indicator. A one-standard-deviation decrease in credit score (=~ 42 points, or 0.42 in the regression) lowers the effect of the policy cap on sales by about 0.8 percentage points (=~ -0.42 x -1.84). The effect of CLTV is larger: a one-standard-deviation increase (=0.169) reduces the policy cap's effect on sales by about 3.8 percentage points (=~.169 x 22.65).[12] In other words, the distribution of loans sold after the policy skews toward those with greater credit risk. Thus, lenders 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 un-tabulated 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.

Table 4 presents the regression results for the interest rate on originated mortgages. Interest rates increase for speculative mortgages during the policy period – by 10-11 basis points – but change little for risky mortgages once we absorb the full set of fixed effects. The rate increase is

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

modest, representing approximately a 3% increase compared to the average interest rate 302 basis points.

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

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

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. Panel A of Figure 4 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. Panel B plots coefficient estimates (β_t) for loan interest rates; here, rates show a small pre-trend before the policy, then rise sharply after implementation.

Tables 5 and 6 show similar directional effects of the policy, regardless of the sub-segment of speculative mortgages (second-home v. investment properties) and lender type (bank v. non-bank).

For second-home mortgages, the probability of sale to GSEs falls by about 9 percentage points, while for investment properties, the probability falls by 32 percentage points (Table 5, column 1). The effect on GSE sales – the direct effect of the policy – exhibits no pre-trend in either sub-segment (Figures 5 and 6, Panel A). Interest rates increase by 12.5 basis points for

second-home mortgages (with no pre-trend, as shown in Figure 5, Panel B) and by 4.5 percentage points for investment mortgages. This latter result, however, is likely *understated*, as Figure 6, Panel B shows a significant pre-trend in the interest rate for the investment property sub-segment. That is, interest rates on investment properties relative to safe mortgages began to fall before the policy was announced. If we compare the difference between investment mortgages and the control group (safe ones) after this trend bottoms out (January 2020), the increase during the implementation period is about 20 basis points.

Table 6 extends the specification by adding interaction terms based on lender type. Here, we find *no differential policy effect* on interest rates between banks and non-banks; this is true for second and investment home mortgages. For investment homes, sales to GSEs do drop more for non-banks than for banks. To understand the selling behavior better by lender type, Table 7 estimates the probability that a loan remains unsold (column 1), and the probability that a loan is sold to a non-GSE entity (column 2), again comparing banks with non-banks. Here we see sharp differences. Banks increase their holdings of both segments of speculative mortgages – they use their access to deposits to fund these loans on balance sheet; non-banks, in contrast, exhibit weak declines in on-balance sheet finance (only significant in the second-home segment). But unlike banks, non-banks become much more likely to sell speculative mortgages to non-GSE buyers when the policy caps are in effect. The magnitude is especially large in the investment segment (Table 7, Panel B). To summarize: both banks and non-banks sharply reduce their sales to GSEs; banks substitute heavily into on-balance sheet financing (with some additional sales to non-GSEs), while non-banks substitute *only* by selling more speculative mortgages to non-GSEs.

Tables 4 through 7 provide some evidence that reduced access to GSEs lowers credit supply for speculative mortgages, as their interest rates rise sharply regardless of originator type.

These tests are incomplete, however, because they take the flow of applications as given. Next, we relax this assumption and analyze how the GSE purchase caps affect mortgage volumes.

3.2 Purchase Caps and Mortgage Volume

We construct a lender-quarter panel dataset, starting with all conforming conventional home purchase and refinance mortgage applications that were approved or denied between 2020Q3 and 2021Q3. We sum across loan amounts to compute the total quantity of credit for each lender-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 conventional conforming home purchase and refinance 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 lender 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 focus on the impact of $Treatment\ (Speculative)_j$, an indicator set to one if more than 7% of a lender's mortgages sold to GSEs are speculative (second-home or investment) in 2020 (i.e., before the

policy announcement). [13] 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. We construct similar treatment-exposure indicators for the risky mortgage caps, but since these caps had little effect at the loan level, we include them as control variables and do not report their coefficients. We also include lender and year-quarter fixed effects. Heteroskedasticity-robust standard errors are clustered at the lender level.

Tables 8 and 9 present the volume results. For speculative mortgages, the coefficient estimates for *Treatment (Speculative) x Implementation* are negative and statistically significant (Table 8, column 1). The effect is quantitatively large, with treated lenders cutting credit by about 18% overall. Consistent with the loan-level pricing results, which suggest a negative supply effect, speculative mortgage quantities fall more at lenders constrained by the GSE Purchase Cap policy. We see similar magnitudes for the two segments of the affected mortgages, second-home and investment mortgages. And magnitudes are similar for originations and applications (compare Panels A and B), suggesting that the decline in credit supply occurs through lower applications rather than higher rejection rates. Lower application volumes may be due both to higher mortgage interest rates, as shown above, and also because lenders reduce marketing in the affected segments.

The results for both safe and risky mortgages are small and generally not statistically significant (Table 8, columns 4 and 5). Along with the pricing results, this non-result helps establish that the drop in speculative credit reflects lower credit supply, rather than some omitted factor correlated with treatment exposure. We could think of the effect on risky and safe mortgage

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[13] The GSEs enforced the policy caps lender-by-lender, so only those lenders who had sold more than 7% prior to the policy would have faced a new constraint.

volumes as 'placebo' tests. Figures IA.1 and IA.2 plot the respective coefficients in a dynamic DiD framework, which shows no evidence of pre-trends in the volume data.

Table 9 reports an augmented model with lender-type interaction effects. As in Table 6, where non-bank originated, speculative mortgages exhibit the *same* price change from the policy, and volumes also respond similarly regardless of lender type. That is, the triple interaction effects are never statistically significant. The policy elicits a similar supply response from both lender types, despite the fact that *only* banks have the option to replace GSE sales with on-balance sheet finance using deposits. But we showed earlier that non-banks dramatically expand their use of mortgage sales to non-GSEs during the policy period (recall Table 7). The results imply that deposit-financing does not offer banks a comparative advantage in mortgage lending in the presence of an active, private securitization option for non-banks. This result helps explain the large increase in market share of non-bank mortgage lenders (Buchak, et al., 2024).

To summarize: the GSE 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 lenders. In contrast, although the caps nominally limit other classes of risky loans, these caps do not bind. As a result, we see no change in GSE sales of risky loans and no evidence of changes in credit supplied to risky borrowers.

3.3 Local Effects

The policy shock presents the opportunity to study whether lenders manage their credit in response to shocks at the local level. As shown in Table 8, lenders restrict credit in the speculative lending market at the portfolio level when GSE caps bind. In this section, we strip out any effect on credit at the portfolio level to address two questions: First, do lenders reallocate credit across

markets (i.e., away from more exposed and toward less exposed ones)? Second, are there local spillovers to lending segments that are not directly affected by the policy? For the latter analysis, we consider small business lending, where we have lender-market data (for banks). Information synergies could motivate banks to cut back across multiple kinds of local loans in response to a decline in mortgage credit. For example, if a bank withdraws from the speculative mortgage market due to the policy caps, it may also reduce other kinds of credit. Or, borrowers may experience negative housing wealth effects from the decline in mortgage supply, which could in turn spill over and reduce demand for and supply of small business credit, if housing collateral matters for lending decisions (Schmalz, et. al., 2017).[14]

To isolate the local channel, rather than estimate the overall effects at the loan or portfolio level, we now test for effects *within* a given lender 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 lender-market level. This approach allows us to absorb potentially confounding effects at both the market-level and the lender-level (since we can construct a three-dimensional panel and absorb confounds with granular fixed effects). To do so, we focus on originations of speculative mortgages as well as originations of small business loans. With these data, we estimate panel models as follows:

$$Ln(Speculative\ Originations)_{j,c,t} = \gamma_{j,t} + \mu_{c,t} + \eta_{c,j} \qquad \qquad Eq.\ 3a$$
$$+ \beta_1(Announcement_t \times Treatment\ (Speculative)_j)$$
$$+ \beta_2(Implementation_t \times Treatment\ (Speculative)_j)$$
$$+ Control\ Variables + \varepsilon_{j,c,t}\ ,$$

and

$$Ln(Small\ Business\ Loans)_{j,c,t} = \gamma_{j,t} + \mu_{c,t} + \eta_{c,j} \qquad \qquad Eq.\ 3b$$

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[14] We report evidence on housing prices in the last section.

$$+ \beta_1(Post_t \text{ x } Treatment \text{ } (Speculative)_j)$$

$$+ \text{ } Control \text{ } Variables + \varepsilon_{j,c,t} \text{ .}$$

We estimate the model first for speculative mortgages (Equation 3a), sub-divided into second-home and investment properties. Second, we estimate the model for small business lending (Equation 3b). The panel varies across lenders (j), counties (c), and time (t), where time is measured quarterly for mortgages and annually for small business loan.[15] *Announcement* and *Implementation* are defined as above, while *Post* equals one for 2021, the year which includes the quarters of policy announcement and implementation; we use the year 2020 as the reference group. We estimate the regressions with and without branch interaction terms to test whether the policy effects differ by a lender's physical presence in the market.[16] We also control for 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).[17] Banks receive ratings from the Federal regulators based on the 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.[18]

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[15] This analysis focuses on banks because the small business data are only available for them; also, these data are available at the annual frequency, unlike the mortgage data.

[16] We utilize the FDIC Summary of Deposits data to determine if a bank has a branch presence in a specific county.

[17] 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 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%.

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

Since these models are estimated with lender-time fixed effects (due to inclusion of $\gamma_{j,t}$), we are comparing how varying exposure to the policy cap across different markets correlates with lending decisions. Identification comes from reallocation across markets because the $\gamma_{j,t}$ effects fully control for portfolio-level variation in potentially confounding variables. Hence, we do not need to worry about heterogeneity at the lender level. We also remove variation in local credit demand by absorbing county-time fixed effects ($\mu_{c,t}$), as well as variation in a bank's overall importance to a county ($\eta_{c,j}$).[19] We build *Treatment (Speculative)* to capture the bank's market-by-market exposure to the policy caps on speculative mortgages based whether or not the ratio of its 2020 speculative loans sold to the GSEs in market *c* exceeds the 7% cap. Since we include both lender-time fixed effects and lender-geography fixed effects, reasonable control variables that we could potentially add to the regression are absorbed. Our coefficient of interest, β_1, tests whether lenders move funds away from more-affected markets due to the policy.

To test whether the policy spills over to other types of local loans, we focus on small business loans. We obtain small business loan data from the Community Reinvestment Act (CRA) database, provided by the FFIEC. 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. The CRA data also has information on which counties are CRA assessment areas for each bank, which we include in the regression as a dummy variable that is interacted with the policy shock variables.

The results in Tables 10 and 11 provide strong evidence that lenders reduce their exposure to both speculative mortgages (the direct effect of the policy) and small business lending (the

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[19] The results are similar when we exclude bank by county fixed effects.

indirect effect) most in those markets where they are exposed to the purchase caps. For speculative mortgages (Table 10), the effect is slightly larger at the local level than at the portfolio level (22% v. 18% decline), perhaps because some lenders increase speculative mortgage provision in localities below the cap, as well as decreasing them in areas above the cap. (The difference-in-differences empirical design can only identify a relative comparison across more v. less treated market.) Moreover, the coefficients suggest that local reallocation begins to occur at the announcement of the policy, while the overall portfolio effects only emerge after implementation. The timing difference may be driven by the lender-level aggregation across markets where the cap binds and those where it does not. In the subset of data with just bank lenders, we find little impact of whether or not the bank has one or more branches in the local area (columns 3 and 6). Note that the economic magnitude of the policy effect is very similar in the bank subset, consistent with our earlier findings that banks and non-banks respond similarly to the policy.[20]

Table 11 reports similar specifications for small business loan originations, although these tests are, due to data limitations, estimated at the annual frequency. These results suggest that markets where banks are exposed to the policy cap experience declines in small business lending. The policy effect attenuates when we control for local branch presence, but we observe no interaction between the policy effect and whether or not a bank has a local branch. The attenuation could occur, in part, if banks are more likely to close branches in markets affected by the policy caps, since small business lending declines with (exogenous) branch closures (Nguyen, 2019). The banking system overall began cutting branches in 2009, and the rate of decline accelerated after the pandemic. The removal of the GSE subsidy could plausibly have led some banks to close

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[20] Figure IA.3 presents dynamic DiD regression results to support the causal interpretation as there is no visible pre-tend in lending activity.

branches in those areas that were most affected sooner than in other areas. In fact, we do see a negative correlation between the number of branches and treatment exposure, although this effect is weak, statistically (untabulated).

Taken together, these results suggest that lenders respond to the policy caps on speculative mortgages by reducing lending in the more-exposed markets. This decline is also associated with a decline in small business lending, perhaps because the loss of the GSE subsidy encourages banks to reduce their overall business in those areas (and hence closing branches). Beyond this explanation, the decline in credit for speculative mortgages could reduce housing prices and thus local wealth, which would in turn reduce demand for small business credit. We turn to this next.

3.4 GSE Purchase Cap Policy, Housing, and Real Effects

In this section we consider the broader potential local effects of the purchase caps, such as how both housing prices and housing transactions by different types of investors respond to the policy. Based on the 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). We end by testing 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, using the shares and the transaction volume subdivided into mortgaged speculative transactions, cash speculative transactions, corporate transactions, and primary transactions, as the outcome variables.[21] Speculative transactions are defined as non-owner-

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[21] One concern with the tract-level analysis 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

occupied home purchases. CoreLogic provides information on whether the transaction is by cash, which we use to further classify speculative transactions into cash speculative transactions and mortgaged speculative transactions. 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). [22] Corporate transactions are defined based on whether houses are purchased by corporate buyers, as indicated in the raw data by CoreLogic. Primary residence 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.

Panel A of Table 12 presents the regression results for the tract-level percentage of mortgaged speculative transactions, cash speculative transactions, primary transactions, and corporate transactions. Here, we estimate treatment exposure (*Treatment Intensity*) based on the fraction of speculative mortgages sold to GSEs during the pre-period by tract. Since many lenders may operate in a given tract, there is no clear way to use the sharp 7% cutoff. We include the county-level total number of COVID-19 cases and deaths in each quarter to control for pandemic-induced housing demand. The coefficient estimates for *Announcement x Treatment Intensity* and *Implementation x Treatment Intensity* are negative and statistically significant, suggesting that the percentage of mortgaged second/investment home transactions drops more for tracts with higher exposure to the GSE Purchase Cap policy. Economically, a one standard deviation increase in

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speculation (treatment intensity) 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.

[22] We cannot use the approach (buy and sell within 3 years) from Defusco, Nathanson, and Zwick (2022) because of our limited sample period.

treatment intensity for a given tract reduces the percentage of second/investment home transactions by 57 basis points (bps) (= 0.15 x 0.038), a 3.3% drop compared to the sample average percentage of mortgaged second/investment home transactions (17%). Consistent with the policy affecting only on mortgages, the coefficient estimates for *Announcement x Treatment Intensity* and *Implementation x Treatment Intensity* are statistically insignificant with a magnitude close to zero for cash speculative transactions. 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. 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 12 reports transaction volumes using the number of transactions (rather than percentages). Transaction volumes have a strong seasonal component that varies across markets, so we remove this variation, following the procedure outlined in Berger et al. (2020).[23] These results establish actual substitution away from mortgaged speculative transactions and toward primary residence transactions, rather than just a proportional decline in speculative activity. The magnitude of the increase in primary residence transactions more than offsets the decline in speculative transactions, which may reflect less competition in the housing market for

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[23] 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 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.

primary homebuyers as credit becoming less available for speculative homebuyers. In addition, the increase in transaction activity by corporate investors (column 4), 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.4 suggests little evidence of any pre-trends.

Table 13 reports similar tract-level regression results of house price growth. These results 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 that do not rely on GSE subsidies (as shown in Table 12). Consistent with the evidence on transaction volumes, Figure IA.5 shows an absence of any pre-trend.

Table 14 tests for real effects. In particular, we test whether activity in the home building industry falls in localities that are more affected by the policy caps. We explore three outcomes: wage and employment in the construction industry and building permits for one-unit homes. We keep the same five quarters as our 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 to 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 COVID-19 pandemic, credit supply declined in the affected markets, as expected. Lenders reallocate credit for speculative mortgages away from markets where they are most exposed to the policy; these adjustments, in turn, also lead to declines in small business lending. The local empirical design sweeps out portfolio-level effects with granular lender-time fixed effects. As such, the evidence suggests that lenders manage credit not only in a macro sense, which has been the main focus of the banking literature, but also market-by-market. The supply response of banks v. non-banks exhibits no difference, suggesting that deposits do not provide banks with any comparative advantage over non-banks in mortgage lending, as non-banks are able to aggressively substitute into the non-GSE securitization market.

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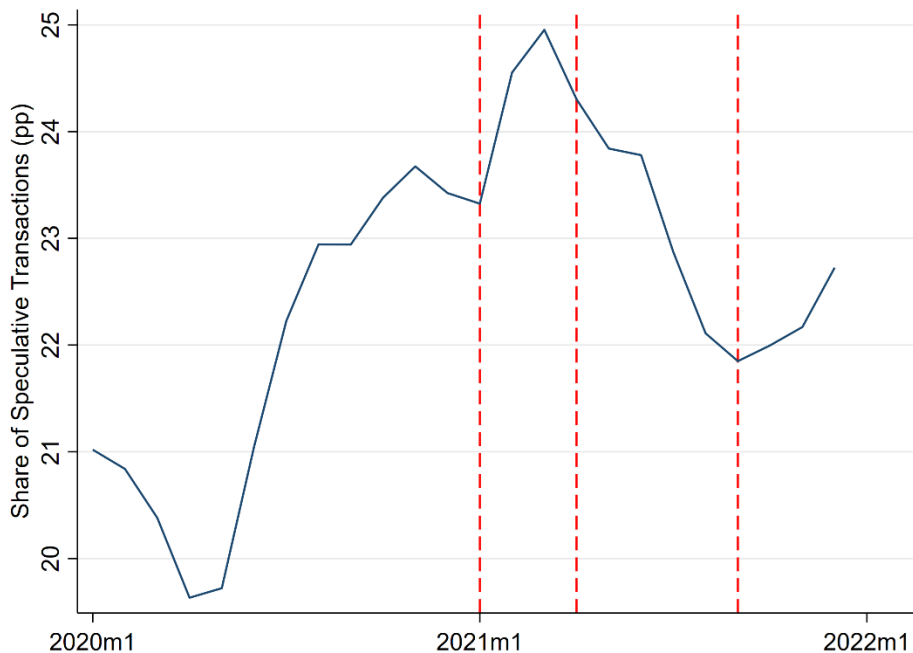
Figure 1: Nationwide Fractions of Speculative Transactions

Figure 1 presents the nationwide seasonality-adjusted trends of speculative transactions, spanning 2020 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 prior, following Berger et al. (2020). The three vertical lines indicate the announcement, implementation, and termination of the GSE Purchase Cap policy, respectively. Data source: CoreLogic.

Panel A: Breakdown of GSEs' Mortgage Purchases by Category

Legend: Speculative; Risky Purchase; Risky Refi
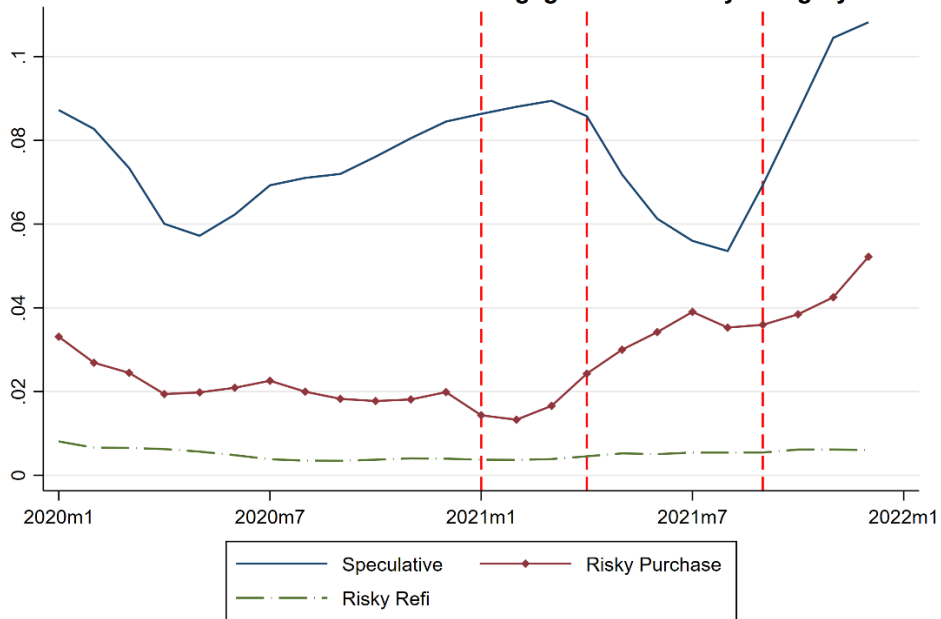
Panel B: Share of Originated Loans Sold to the GSEs

Legend: Speculative; Risky

Panel C: Share of Originated Mortgages Unsold
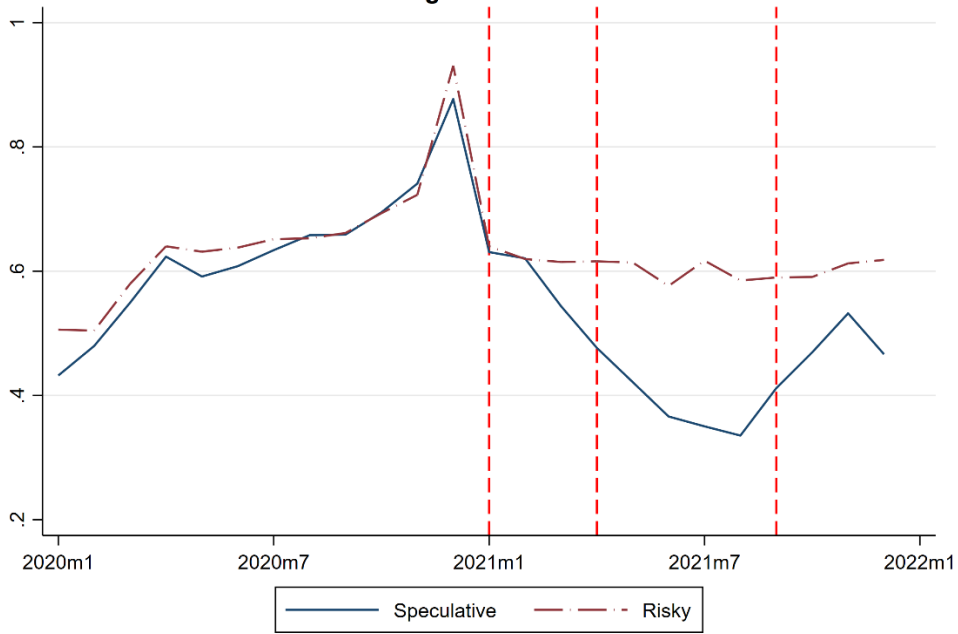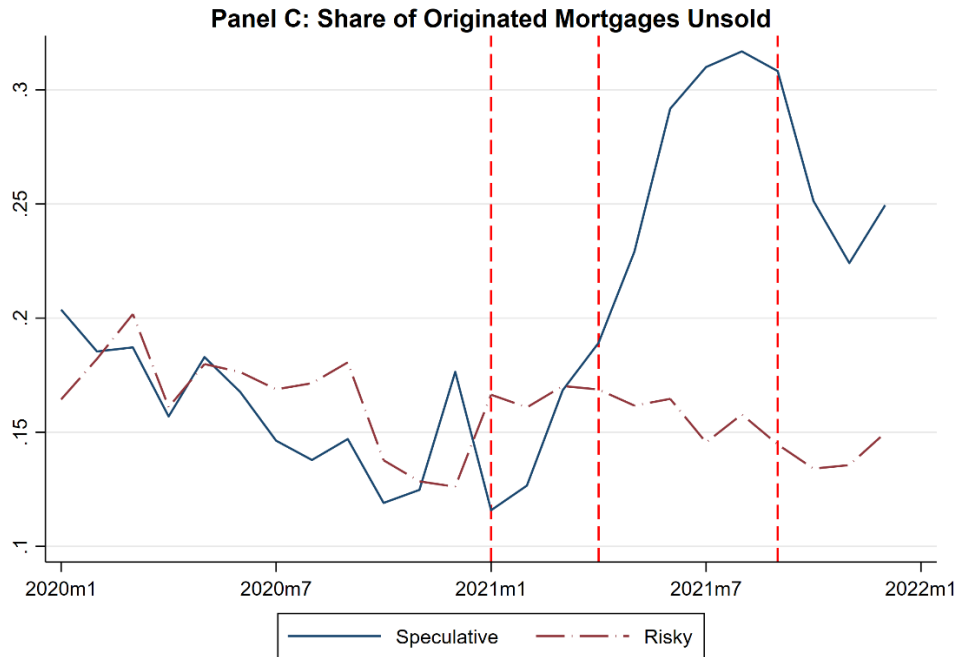
Figure 2: Time Series Plots of CHMDA Mortgage Trends

Panels A through C present nationwide trends in the conforming mortgage loan market. Panel A shows the speculative (home purchase and refinance combined), risky home purchase, and risky refinance mortgage loans that are sold to the GSEs as fractions of all mortgage loans sold to the GSEs. Speculative loans are mortgages that are backed by second or investment homes. Panel B shows the share of originated speculative and risky mortgage loans sold to the GSEs. Panel C plots the share of originated speculative and risky loans held on lenders' balance sheets. Conforming mortgages can be sold to the GSEs, sold to non-GSE entities, or held on the lenders' balance sheets. To account for seasonality in sale probability, induced by CHMDA's reporting convention, Panels B and C have been seasonally adjusted using the prior 24-month seasonality factors. Panel A is not adjusted for seasonality in sale probability because the sample only includes mortgages that have been sold to the GSEs. 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

Nationwide
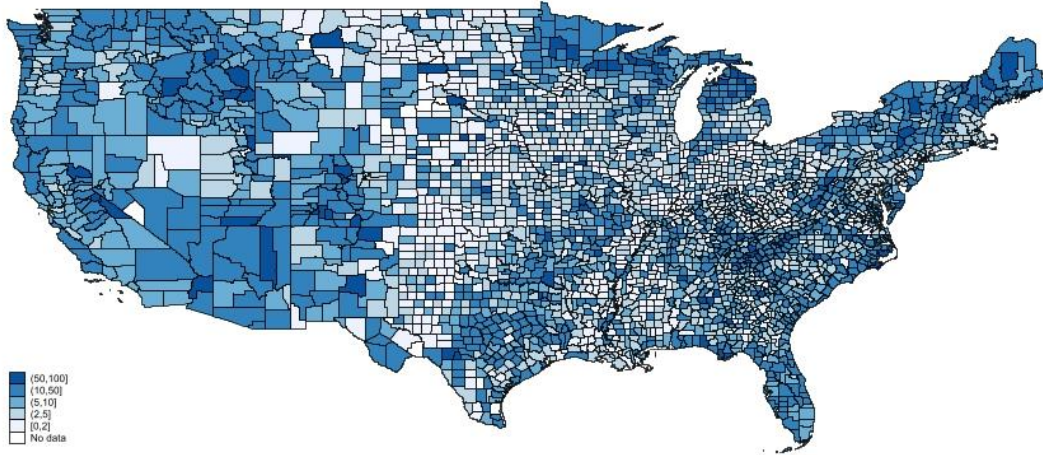
Panel B: Tract-Level Exposure in Major Cities

Boston   Chicago   New York City
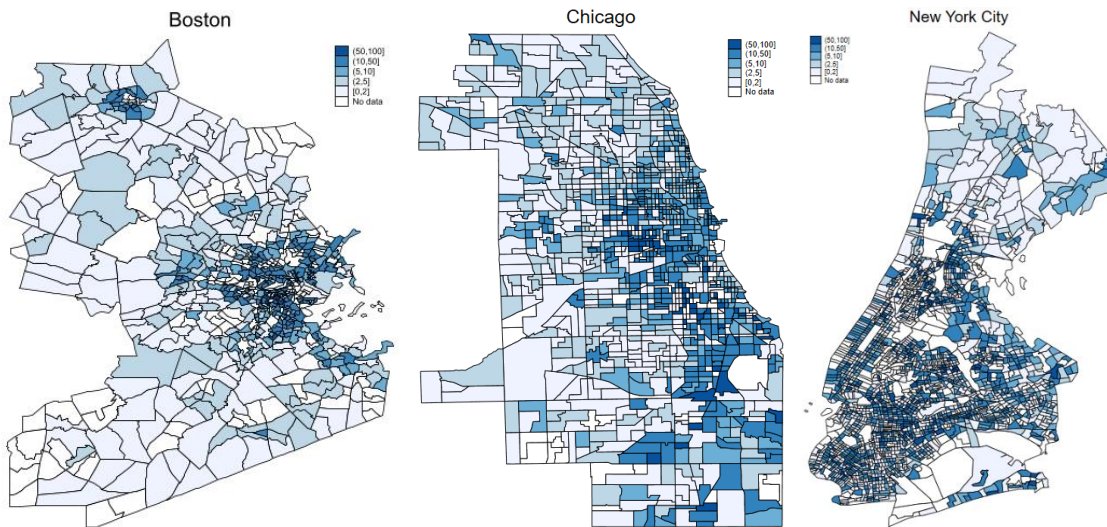
Figure 3. Geographic Exposure to the GSE Purchase Cap Policy

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 and 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 and investment home backed mortgages that the GSEs purchased in each census tract in 2020.

Panel A: P(GSE Sale) x 100

Panel B: Interest Rate (bps)

Figure 4. Loan-Level Parallel Trend Regressions – Speculative Mortgages

Panel A plots regression coefficients and their 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 backed by second or investment homes and zero otherwise. The reference group is composed of "safe" conforming mortgages. The sample includes home purchase and refinance mortgages. The outcome variable equals 100 if the mortgage was sold to Fannie Mae or Freddie Mac by the end of the reporting calendar year and zero otherwise. The regression specification includes control variables outlined in the Internet Appendix, lender by year-month and tract fixed effects. The sample includes conforming home purchase and refinance mortgages that were originated between 2020Q3 and 2021Q3. The vertical dotted lines mark the month in which the GSE purchase cap policy was announced and implemented. Heteroskedasticity-robust standard errors are clustered at the lender level. Panel B plots the interest rate regression result. The outcome variable is the mortgage's interest rate, expressed in basis points. Data source: CHMDA.

Panel A: P(GSE Sale) x 100

Panel B: Interest Rate (bps)

Figure 5. Loan-Level Parallel Trend Regressions – Second Home Mortgages

Panel A plots regression coefficients and their 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 homes and zero otherwise. The reference group is composed of "safe" conforming mortgage applications. The sample includes home purchase and refinance mortgages. The outcome variable equals 100 if the mortgage was sold to Fannie Mae or Freddie Mac by the end of the reporting calendar year and zero otherwise. The regression specification includes control variables outlined in the Internet Appendix, lender by year-month, and tract fixed effects. The sample includes conforming home purchase and refinance mortgages that were originated between 2020Q3 and 2021Q3. The vertical dotted lines mark the month in which the GSE purchase cap policy was announced and implemented. Heteroskedasticity-robust standard errors are clustered at the lender level. Panel B plots the interest rate regression result. The outcome variable is the mortgage's interest rate, expressed in basis points. Data source: CHMDA.

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Panel A: P(GSE Sale) x 100
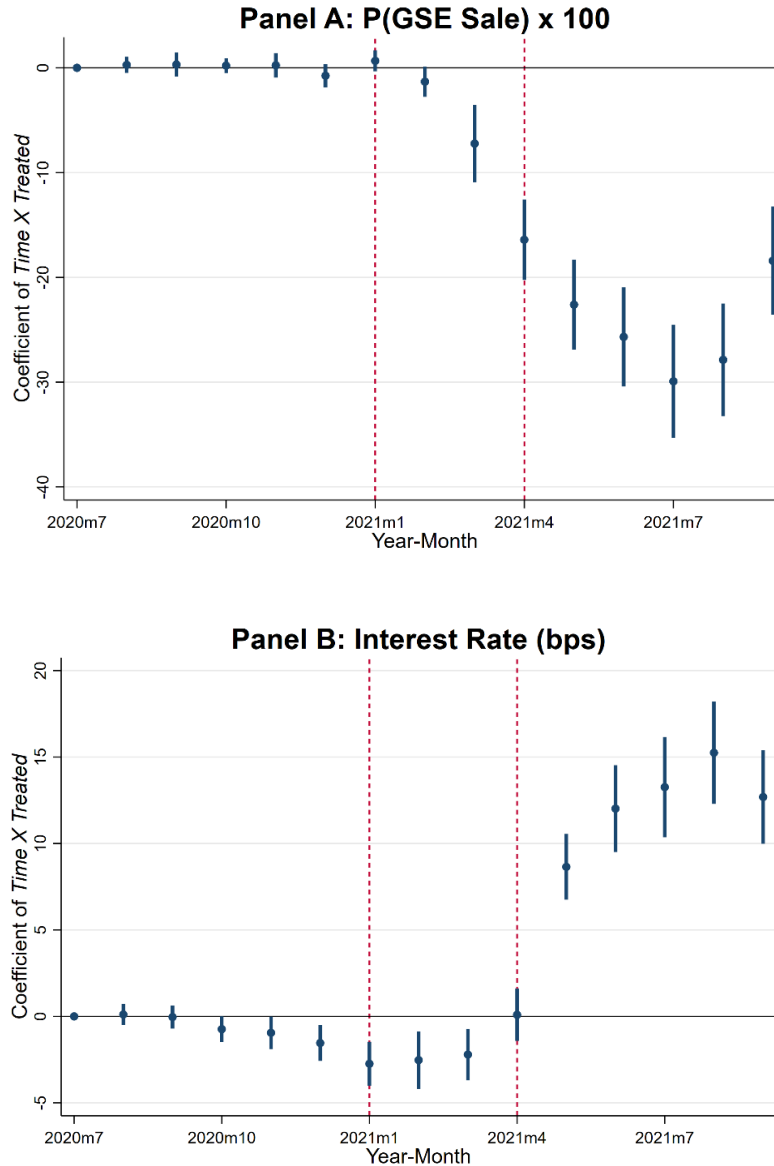

Panel B: Interest Rate (bps)

Figure 6. Loan-Level Parallel Trend Regressions – Investment Home Mortgage

Panel A plots regression coefficients and their 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 investment homes and zero otherwise. The reference group is composed of "safe" conforming mortgage applications. The sample includes home purchase and refinance mortgages. The outcome variable equals 100 if the mortgage was sold to Fannie Mae or Freddie Mac by the end of the reporting calendar year and zero otherwise. The regression specification includes control variables outlined in the Internet Appendix, lender by year-month, and tract fixed effects. The sample includes conforming home purchase and refinance mortgages that were originated between 2020Q3 and 2021Q3. The vertical dotted lines mark the month in which the GSE purchase cap policy was announced and implemented. Heteroskedasticity-robust standard errors are clustered at the lender level. Panel B plots the interest rate regression result. The outcome variable is the mortgage's interest rate, expressed in basis points. Data source: CHMDA.
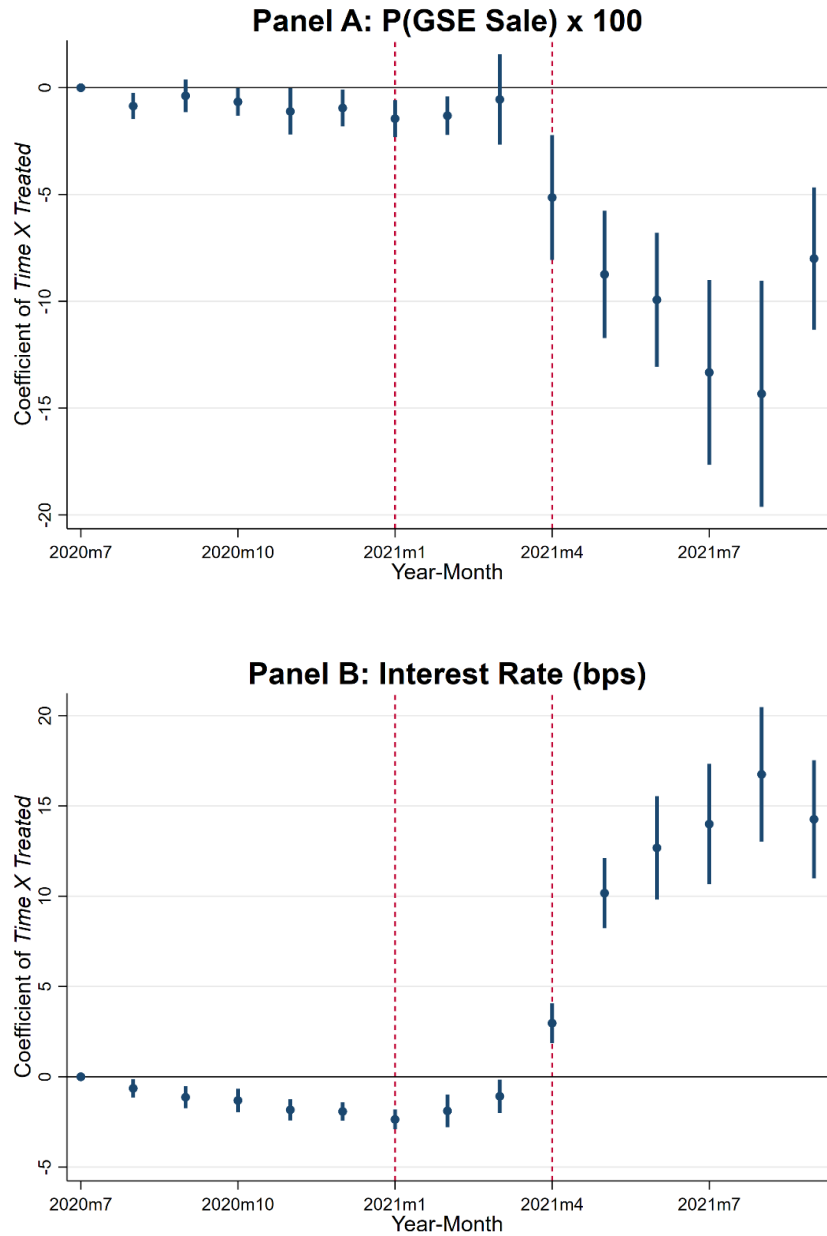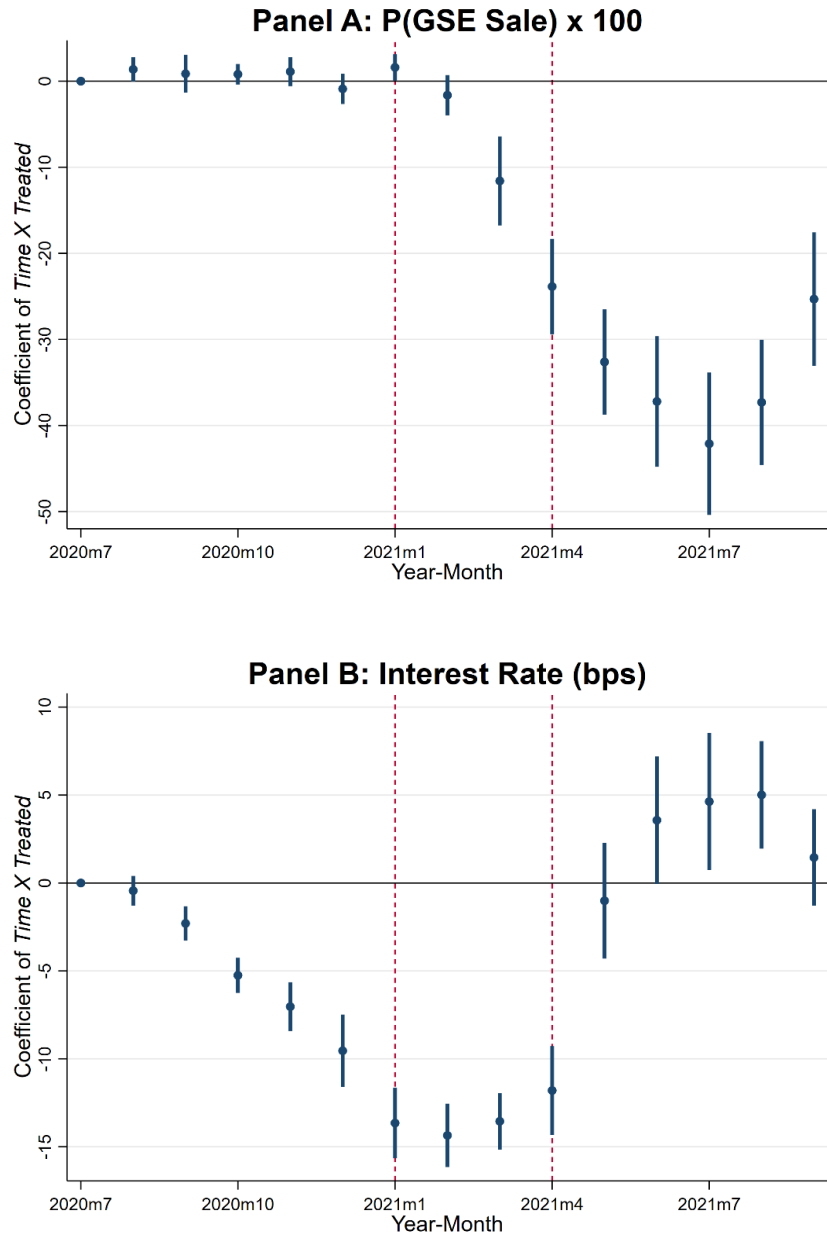
Table 1. Summary Statistics

This table presents summary statistics for the various data samples that we use in our analyses. The sample period is from 2020Q3 to 2021Q3. Panels A presents summary statistics on the loan-level sample constructed from CHMDA. Panels B presents summary statistics on the lender-quarter-level sample constructed from CHMDA. Panels C presents summary statistics on the lender-county-quarter-level sample constructed from CHMDA, FDIC Summary of Deposits, and FFIEC data. Panels D presents summary statistics on the tract-quarter-level sample constructed from CHMDA and CoreLogic. Panels E presents summary statistics on the county-quarter-level sample constructed from CHMDA, Census Building Permit Survey, and Bureau of Labor Statistics Quarterly Census of Employment and Wages. Refer to the Internet Appendix for additional details on variable definitions. Dollar values are reported in nominal terms. Data sources: CHMDA, FFIEC, FDIC, CoreLogic, Census Building Permit Survey, and Bureau of Labor Statistics Quarterly Census of Employment and Wages.

	Mean	Median	S.D.	N
	(1)	(2)	(3)	(4)
Panel A: Loan Level				
GSE Sale	0.66	1.00	0.47	6,805,482
Unsold	0.11	0.00	0.31	6,805,482
Non-GSE Sale	0.23	0.00	0.42	6,805,482
Interest Rate (bps)	302.36	299.00	34.77	6,802,556
Policy Exposure (Loan)				
Second Home Mortgage	0.04	0.00	0.21	6,805,482
Investment Home Mortgage	0.06	0.00	0.24	6,805,482
Risky Mortgage	0.04	0.00	0.19	6,805,482
Panel B: Lender-Quarter Level				
Second Home Mortgage Application Volume (USD Millions)	11.99	2.47	26.08	7,247
Investment Home Mortgage Application Volume (USD Millions)	14.4	3.25	30.73	7,708
Risky Mortgage Application Volume (USD Millions)	19.3	3.75	47.94	6,415
Safe Mortgage Application Volume (USD Millions)	185.74	40.37	370.24	8,299
Second Home Mortgage Application Volume (USD Millions)	10.87	2.29	23.25	7,104
Investment Home Mortgage Application Volume (USD Millions)	12.5	2.97	26.26	7,582
Risky Mortgage Application Volume (USD Millions)	14	2.63	33.28	6,050
Safe Mortgage Application Volume (USD Millions)	167.76	35.95	334.14	8,290
Non-Bank	0.24	0	0.43	8,336
Policy Exposure (Lender)				
Speculative Mortgage Treatment	0.47	0	0.5	8,560
Risky Home Purchase Mortgage Treatment	0.09	0	0.28	8,560
Risky Refinance Mortgage Treatment	0.03	0	0.17	8,560
Panel C: Lender-County-Quarter Level				
Second Home Mortgage Application Volume (USD Millions)	0.66	0.34	1.03	148,322
Investment Home Mortgage Application Volume (USD Millions)	0.78	0.30	1.49	150,717
Small Business Loan Volume (USD Millions)	3.81	0.37	11.57	108,978
Bank	0.44	0	0.5	229,458
Branch	0.15	0	0.36	239,073
CRA Assessment Area	0.02	0	0.15	239,073
Policy Exposure (Lender-County)				
Speculative Mortgage Treatment	0.54	1	0.5	239,073

Risky Home Purchase Mortgage Treatment	0.15	0	0.36	239,073
Risky Refinance Mortgage Treatment	0.06	0	0.24	239,073
Panel D: Tract-Quarter Level				
# Mortgaged Speculative Transactions	2.82	1.23	4.02	324,433
# Cash Speculative Transactions	1.08	0.00	1.75	324,433
# Primary Transactions	12.44	8.69	13.17	324,433
# Corporate Transactions	1.72	0.94	2.30	324,433
% Mortgaged Speculative Transactions	0.17	0.09	0.22	324,433
% Cash Speculative Transactions	0.06	0.00	0.11	324,433
% Primary Transactions	0.63	0.70	0.29	324,433
% Corporate Transactions	0.10	0.06	0.15	324,433
Average House Price ($)	387,642	283,006	341,674	324,433
Median House Price ($)	360,134	266,000	310,882	324,433
Average House Price Growth	0.04	0.04	0.28	317,598
Median House Price Growth	0.04	0.04	0.27	317,598
Policy exposure (Tract)				
Treatment Intensity	0.10	0.05	0.15	324,433
Panel E: County-Quarter Level				
One-Unit Permit Growth	0.01	0.00	0.70	3,569
Average Construction Wage Growth	0.01	0.00	0.60	14,596
Construction Employment Growth	0.02	0.00	0.60	14,596
Policy exposure (County)				
Treatment Intensity	0.11	0.05	0.15	14,596

Table 2. GSE Purchase Cap and GSE Sale Probability

This table presents loan-level OLS regression results where the GSE sale indicator variable is regressed onto GSE purchase cap policy shock indicator variables. The outcome variable equals 100 if the mortgage was sold to Fannie Mae or Freddie Mac by the end of the reporting calendar year and zero otherwise. In Panel A, Speculative equals one for mortgages associated with second or investment homes and zero for safe mortgages associated with primary residences. In Panel B, Risky equals one for risky mortgages associated with primary residences and zero for safe mortgages associated with primary residences. Refer to the main text for details on the definition of risky. Announcement equals one for 2021Q1 and zero otherwise. Implementation equals one for 2021Q2 and 2021Q3 and zero otherwise. The sample includes conforming home purchase and refinance 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 source: CHMDA.

Panel A: Speculative v. Safe

	GSE Sale		
	(1)	(2)	(3)
Speculative	-1.04	0.68	0.29
	[1.04]	[0.46]	[0.40]
Speculative x Announcement	-3.78***	-3.65***	-2.99***
	[1.13]	[0.89]	[0.98]
Speculative x Implementation	-19.48***	-23.15***	-22.71***
	[2.00]	[2.15]	[2.30]
Controls x Loan Purpose FE	Y	Y	Y
Tract FE	Y	Y	Y
Year-Quarter FE	Y	Y	
Lender FE		Y	
Lender x Year-Quarter FE			Y
Observations	6,556,469	6,556,426	6,556,069
R-squared	0.12	0.55	0.61

Panel B: Risky v. Safe

	GSE Sale		
	(1)	(2)	(3)
Risky	0.57	0.57	0.44
	[1.17]	[0.45]	[0.36]
Risky x Announcement	-0.45	0.16	0.62*
	[0.92]	[0.53]	[0.34]
Risky x Implementation	-0.15	0.55	0.63
	[0.82]	[0.58]	[0.46]
Controls x Loan Purpose FE	Y	Y	Y
Tract FE	Y	Y	Y
Year-Quarter FE	Y	Y	
Lender FE		Y	
Lender x Year-Quarter FE			Y
Observations	6,076,949	6,076,900	6,076,528
R-squared	0.12	0.57	0.62

Table 3. GSE Purchase Cap, 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 the 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 residences. 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 divided by 100. 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 and refinance 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 source: CHMDA.

	GSE Sale	
	(1)	(2)
Speculative	-3.67*	1.57
	[2.19]	[2.16]
Speculative x Announcement	-0.96	-8.17**
	[3.64]	[3.96]
Speculative x Implementation	-14.12**	-22.85***
	[6.52]	[7.83]
Speculative x Credit Score	0.24	-0.17
	[0.26]	[0.25]
Speculative x Announcement x Credit Score	-0.71	0.09
	[0.46]	[0.46]
Speculative x Implementation x Credit Score	-2.71***	-1.84**
	[0.67]	[0.74]
Speculative x CLTV	4.03**	0.72
	[1.60]	[1.39]
Speculative x Announcement x CLTV	5.44**	7.04***
	[2.22]	[2.24]
Speculative x Implementation x CLTV	19.03***	22.65***
	[5.00]	[5.41]
Speculative x DTI	-1.66	-1.69
	[1.08]	[1.07]
Speculative x Announcement x DTI	-0.71	-0.55
	[2.12]	[2.12]
Speculative x Implementation x DTI	-3.83	-3.82
	[3.82]	[3.79]
Controls x Loan Purpose FE	Y	Y
Tract FE	Y	Y
Lender x Year-Quarter FE	Y	Y
LLPA x Year-Quarter FE		Y
SE Cluster	Lender	Lender
Observations	6,500,542	6,500,537
R-squared	0.60	0.60

Table 4. GSE Purchase Cap and Interest Rate

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 residences. In Panel B, Risky equals one for risky mortgages associated with primary residences and zero for safe mortgages associated with primary residences. Refer to the main text for details on the definition of risky. Announcement equals one for 2021Q1 and zero otherwise. Implementation equals one for 2021Q2 and 2021Q3 and zero otherwise. The sample includes conforming home purchase and refinance 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 source: CHMDA.

Panel A: Speculative v. Safe

	Interest Rate (bps)		
	(1)	(2)	(3)
Speculative	28.82***	28.91***	29.37***
	[0.74]	[0.80]	[0.80]
Speculative x Announcement	-1.32***	-1.31***	-1.42**
	[0.46]	[0.50]	[0.61]
Speculative x Implementation	10.91***	11.19***	10.50***
	[1.16]	[0.94]	[0.97]
Controls x Loan Purpose FE	Y	Y	Y
Tract FE	Y	Y	Y
Year-Quarter FE	Y	Y	
Lender FE		Y	
Lender x Year-Quarter FE			Y
Observations	6,553,829	6,553,786	6,553,426
R-squared	0.40	0.47	0.50

Panel B: Risky v. Safe

	Interest Rate (bps)		
	(1)	(2)	(3)
Risky	-1.50*	-1.53**	-0.71
	[0.79]	[0.75]	[0.78]
Risky x Announcement	-1.27***	-1.02*	-1.15**
	[0.49]	[0.53]	[0.57]
Risky x Implementation	2.01***	2.38***	0.74
	[0.73]	[0.74]	[0.74]
Controls x Loan Purpose FE	Y	Y	Y
Tract FE	Y	Y	Y
Year-Quarter FE	Y	Y	
Lender FE		Y	
Lender x Year-Quarter FE			Y
Observations	6,074,529	6,074,480	6,074,110
R-squared	0.37	0.46	0.49

Table 5. GSE Purchase Cap, Second and Investment Home Mortgage GSE Sale Probability and Interest Rate

This table presents mortgage-level OLS regression results where GSE sale indicator variable or interest rate is regressed onto GSE purchase cap policy shock indicator variables. GSE Sale equals 100 if the mortgage was sold to Fannie Mae or Freddie Mac by the end of the reporting calendar year and zero otherwise. In Panel A, Second equals one for mortgages associated with second homes and zero for safe mortgages associated with primary residences. In Panel B, Investment equals one for mortgages associated with investment homes and zero for safe mortgages associated with primary residences. Announcement equals one for 2021Q1 and zero otherwise. Implementation equals one for 2021Q2 and 2021Q3 and zero otherwise. The sample includes conforming home purchase and refinance 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 source: CHMDA.

Panel A: Second Home v. Safe

	GSE Sale	Interest Rate (bps)
	(1)	(2)
Second	0.52**	-0.10
	[0.22]	[0.22]
Second x Announcement	-0.45	-0.25
	[0.47]	[0.30]
Second x Implementation	-8.92***	12.54***
	[1.39]	[1.24]
Controls x Loan Purpose FE	Y	Y
Tract FE	Y	Y
Lender x Year-Quarter FE	Y	Y
Observations	6,131,811	6,129,544
R-squared	0.62	0.48

Panel B: Investment Home v. Safe

	GSE Sale	Interest Rate (bps)
	(1)	(2)
Investment	0.48	52.34***
	[0.62]	[1.10]
Investment x Announcement	-4.80***	-8.54***
	[1.42]	[0.63]
Investment x Implementation	-32.27***	4.53***
	[3.45]	[1.09]
Controls x Loan Purpose FE	Y	Y
Tract FE	Y	Y
Lender x Year-Quarter FE	Y	Y
Observations	6,256,499	6,254,001
R-squared	0.61	0.54

Table 6. GSE Purchase Cap, Second and Investment Home Mortgage GSE Sale Probability and Interest Rate – Bank versus Non-Bank

This table presents mortgage-level OLS regression results where GSE sale indicator variable or interest rate is regressed onto GSE purchase cap policy shock indicator variables. GSE Sale equals 100 if the mortgage was sold to Fannie Mae or Freddie Mac by the end of the reporting calendar year and zero otherwise. In Panel A, Second equals one for mortgages associated with second homes and zero for safe mortgages associated with primary residences. In Panel B, Investment equals one for mortgages associated with investment homes and zero for safe mortgages associated with primary residences. Announcement equals one for 2021Q1 and zero otherwise. Implementation equals one for 2021Q2 and 2021Q3 and zero otherwise. Non-Bank equals one if the lender is not a depository institution according to the Avery file and zero otherwise. The sample includes conforming home purchase and refinance 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 source: CHMDA.

Panel A: Second Home v. Safe

	GSE Sale	Interest Rate (bps)
	(1)	(2)
Second	-0.13	-2.13***
	[0.45]	[0.46]
Second x Non-Bank	0.93	3.07***
	[0.64]	[0.65]
Second x Announcement	-0.38	-0.09
	[0.52]	[0.36]
Second x Implementation	-9.13***	10.79***
	[1.67]	[0.92]
Second x Non-Bank x Announcement	-0.09	-0.29
	[0.82]	[0.60]
Second x Non-Bank x Implementation	0.52	2.17
	[2.56]	[2.18]
Controls x Loan Purpose FE	Y	Y
Tract FE	Y	Y
Lender x Year-Quarter FE	Y	Y
Observations	5,896,405	5,894,230
R-squared	0.62	0.48

Panel B: Investment Home v. Safe		
	GSE Sale	Interest Rate (bps)
	(1)	(2)
Investment	0.00	56.05***
	[1.14]	[0.89]
Investment x Non-Bank	0.50	-5.19***
	[1.38]	[1.36]
Investment x Announcement	-2.97	-7.30***
	[3.45]	[0.63]
Investment x Implementation	-20.31***	5.60***
	[5.60]	[1.42]
Investment x Non-Bank x Announcement	-2.53	-1.48
	[3.82]	[1.03]
Investment x Non-Bank x Implementation	-16.33**	-1.47
	[7.01]	[1.95]
Controls x Loan Purpose FE	Y	Y
Tract FE	Y	Y
Lender x Year-Quarter FE	Y	Y
Observations	6,018,188	6,015,886
R-squared	0.61	0.54

Table 7. GSE Purchase Cap, Unsold and Sales to non-GSEs – Bank versus Non-Bank

This table presents application/mortgage-level OLS regression results where unsold or non-GSE sale indicator variable is regressed onto GSE purchase cap policy shock indicator variables. Unsold equals 100 if the mortgage was not sold by the end of the reporting calendar year and zero otherwise. Non-GSE Sale equals 100 if the mortgage was sold to a non-GSE entity by the end of the reporting calendar year and zero otherwise. In Panel A, Second equals one for mortgages associated with second homes and zero for safe mortgages associated with primary residences. In Panel B, Investment equals one for mortgages associated with investment homes and zero for safe mortgages associated with primary residences. Announcement equals one for 2021Q1 and zero otherwise. Implementation equals one for 2021Q2 and 2021Q3 and zero otherwise. Non-Bank equals one if the lender is not a depository institution according to the Avery file and zero otherwise. The sample includes conforming home purchase and refinance 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 source: CHMDA.

Panel A: Second Home v. Safe

	Unsold	Non-GSE Sale
	(1)	(2)
Second	-0.16	0.29
	[0.40]	[0.22]
Second x Non-Bank	0.25	-1.18***
	[0.50]	[0.38]
Second x Announcement	1.44***	-1.06***
	[0.37]	[0.37]
Second x Implementation	8.65***	0.48
	[1.65]	[0.73]
Second x Non-Bank x Announcement	-0.89	0.98
	[0.59]	[0.64]
Second x Non-Bank x Implementation	-6.28***	5.76***
	[2.12]	[1.72]
Controls x Loan Purpose FE	Y	Y
Tract FE	Y	Y
Lender x Year-Quarter FE	Y	Y
Observations	5,896,405	5,896,405
R-squared	0.54	0.67

Panel B: Investment Home v. Safe		
	Unsold	Non-GSE Sale
	(1)	(2)
Investment	0.40	-0.40
	[1.00]	[0.78]
Investment x Non-Bank	0.82	-1.31
	[1.02]	[1.02]
Investment x Announcement	2.14	0.83
	[3.35]	[1.50]
Investment x Implementation	13.93**	6.38***
	[5.64]	[1.75]
Investment x Non-Bank x Announcement	-1.18	3.72*
	[3.50]	[1.91]
Investment x Non-Bank x Implementation	-8.85	25.17***
	[6.33]	[5.02]
Controls x Loan Purpose FE	Y	Y
Tract FE	Y	Y
Lender x Year-Quarter FE	Y	Y
Observations	6,018,188	6,018,188
R-squared	0.53	0.66

Table 8. GSE Purchase Cap and Mortgage Credit Supply

This table presents OLS regression results for GSE purchase cap policy treatment and conforming mortgage lending volume. Each observation is a lender by year-quarter. In Panel A, the dependent variables are the natural logarithms of home purchase and refinance mortgage origination volumes. Calculated at the lender level, Treatment (Speculative) equals one if the proportion of the lender's 2020 speculative home purchase and refinance loan amount sold to the GSEs relative to its total conventional conforming home purchase and refinance loan amount sold to the GSEs in 2020 is greater than 7% and zero otherwise. Treatment (Risky Purchase) equals one if the proportion of the lender's 2020 risky home purchase loan amount sold to the GSEs relative to its total conventional conforming home purchase and refinance loan amount sold to the GSEs in 2020 is greater than 6% and zero otherwise. Treatment (Risky Refi) equals one if the proportion of the lender's 2020 risky refinance loan amount sold to the GSEs relative to its total conventional conforming home purchase and refinance loan amount sold to the GSEs in 2020 is greater than 3% and zero otherwise. Announcement equals one for 2021Q1 and zero otherwise. Implementation equals one for 2021Q2 and 2021Q3 and zero otherwise. Panel B presents the results for application volumes. Heteroskedasticity-robust standard errors are clustered at the lender level. *, **, and *** denote 10%, 5%, and 1% statistical significance levels, respectively. Data source: CHMDA.

Panel A: Origination Volume

| | Ln(Origination Volume USD) | | | |
| | Second Home | Investment | Risky | Safe |
	(1)	(2)	(3)	(4)
Announcement x Treatment Dummy	-0.04	0.03	0.05	0.06***
	[0.03]	[0.03]	[0.04]	[0.02]
Implementation x Treatment Dummy	-0.18***	-0.18***	-0.01	0.02
	[0.03]	[0.03]	[0.04]	[0.02]
Risky Treatment Controls	Y	Y	Y	Y
Year-Quarter FE	Y	Y	Y	Y
Lender FE	Y	Y	Y	Y
Observations	7,033	7,540	5,986	8,285
R-squared	0.92	0.92	0.93	0.97

Panel B: Application Volume

| | Ln(Application Volume USD) | | | |
| | Second Home | Investment | Risky | Safe |
	(1)	(2)	(3)	(4)
Announcement x Treatment Dummy	-0.04	0.04	0.02	0.06***
	[0.03]	[0.03]	[0.04]	[0.02]
Implementation x Treatment Dummy	-0.17***	-0.17***	0.02	0.02
	[0.03]	[0.03]	[0.03]	[0.02]
Risky Treatment Controls	Y	Y	Y	Y
Year-Quarter FE	Y	Y	Y	Y
Lender FE	Y	Y	Y	Y
Observations	7,178	7,669	6,383	8,295
R-squared	0.93	0.93	0.94	0.97

Table 9. GSE Purchase Cap Policy and Mortgage Credit Supply – Bank versus Non-Bank

This table presents OLS regression results for GSE purchase cap policy treatment and conforming mortgage lending volume. Each observation is a lender by year-quarter. In Panel A, the dependent variables are the natural logarithms of home purchase and refinance mortgage origination volumes. Calculated at the lender level, Treatment (Speculative) equals one if the proportion of the lender's 2020 speculative home purchase and refinance loan amount sold to the GSEs relative to its total conventional conforming home purchase and refinance loan amount sold to the GSEs in 2020 is greater than 7% and zero otherwise. Treatment (Risky Purchase), Treatment (Risky Refi), and their policy shock interaction terms are included as control variables but omitted from the table. Non-Bank equals one if the lender is not a depository institution according to the Avery file and zero otherwise. Announcement equals one for 2021Q1 and zero otherwise. Implementation equals one for 2021Q2 and 2021Q3 and zero otherwise. Panel B presents the results for application volumes. Heteroskedasticity-robust standard errors are clustered at the tract level. *, **, and *** denote 10%, 5%, and 1% statistical significance levels, respectively. Data source: CHMDA.

Panel A: Origination Volume

	Ln(Origination Volume USD)			
	Second Home	Investment	Risky	Safe
	(1)	(2)	(3)	(4)
Announcement x Treatment (Speculative)	-0.06	0.03	0.03	0.05**
	[0.04]	[0.04]	[0.05]	[0.02]
Implementation x Treatment (Speculative)	-0.18***	-0.13***	-0.06	0.03
	[0.04]	[0.04]	[0.04]	[0.03]
Announcement x Non-Bank	0.21***	0.27***	0.17**	0.07
	[0.06]	[0.06]	[0.07]	[0.05]
Implementation x Non-Bank	-0.12*	-0.21***	0.24***	0.05
	[0.06]	[0.07]	[0.06]	[0.05]
Announcement x Non-Bank x Treatment (Speculative)	-0.04	-0.11	0.03	0.02
	[0.07]	[0.07]	[0.09]	[0.07]
Implementation x Non-Bank x Treatment (Speculative)	0.03	-0.08	0.05	-0.05
	[0.08]	[0.08]	[0.08]	[0.07]
Risky Treatment Controls	Y	Y	Y	Y
Year-Quarter FE	Y	Y	Y	Y
Lender FE	Y	Y	Y	Y
Observations	6,826	7,330	5,783	8,068
R-squared	0.93	0.93	0.93	0.97

Panel B: Application Volume

	Ln(Application Volume USD)			
	Second Home	Investment	Risky	Safe
	(1)	(2)	(3)	(4)
Announcement x Treatment (Speculative)	-0.05	0.04	-0.00	0.05***
	[0.04]	[0.04]	[0.04]	[0.02]
Implementation x Treatment (Speculative)	-0.17***	-0.13***	-0.01	0.03
	[0.04]	[0.04]	[0.04]	[0.03]
Announcement x Non-Bank	0.19***	0.23***	0.11*	0.07
	[0.06]	[0.05]	[0.06]	[0.05]
Implementation x Non-Bank	-0.13**	-0.19***	0.28***	0.05
	[0.06]	[0.06]	[0.06]	[0.05]
Announcement x Non-Bank x Treatment (Speculative)	-0.04	-0.10	0.02	-0.00
	[0.07]	[0.07]	[0.08]	[0.06]
Implementation x Non-Bank x Treatment (Speculative)	0.04	-0.06	-0.00	-0.04
	[0.07]	[0.08]	[0.08]	[0.06]
Observations	6,967	7,456	6,179	8,078
R-squared	0.93	0.93	0.94	0.97
Risky Treatment Controls	Y	Y	Y	Y
Year-Quarter FE	Y	Y	Y	Y
Lender FE	Y	Y	Y	Y

Table 10. Within-Lender Speculative Mortgage Origination

This table presents OLS regression results at the county-lender-quarter level where the natural log of speculative home purchase and refinance mortgage dollar amounts are regressed onto pre-policy lender-county-level policy exposure. Columns (1) – (3) present the results for second home mortgage origination volume. Columns (4) – (6) present the results for investment home mortgage origination volume. Treatment (Speculative) equals one if the lender-county cell's 2020 speculative home purchase and refinance loan amount sold to the GSEs divided by its total conventional conforming home purchase and refinance mortgage sold to the GSEs in 2020 is greater than 7% and zero otherwise. Treatment (Risky Purchase) and Treatment (Risky Refi) are defined in the same manner and included as control variables. Announcement equals one for 2021Q1 and zero otherwise. Implementation equals one for 2021Q2 and 2021Q3 and zero otherwise. Bank equals one if the lender is a bank, according to the Avery file. Refer to the Internet Appendix for additional details on the control variables. 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 source: CHMDA.

	Ln(Second Home)			Ln(Investment Home)		
	(1)	(2)	(3)	(4)	(5)	(6)
Announcement x Treatment (Speculative)	-0.17***	-0.17***	-0.13***	-0.21***	-0.23***	-0.22***
	[0.02]	[0.02]	[0.04]	[0.02]	[0.02]	[0.03]
Implementation x Treatment (Speculative)	-0.22***	-0.21***	-0.20***	-0.21***	-0.23***	-0.17***
	[0.02]	[0.02]	[0.03]	[0.01]	[0.02]	[0.03]
Announcement x Treatment (Speculative) x Bank		0.03			0.04*	
		[0.03]			[0.03]	
Implementation x Treatment (Speculative) x Bank		0.00			0.04*	
		[0.03]			[0.03]	
Branch			0.18			0.13
			[0.14]			[0.14]
Announcement x Branch			0.00			-0.07*
			[0.04]			[0.04]
Implementation x Branch			-0.08*			-0.02
			[0.04]			[0.04]
Branch x Treatment (Speculative)			-0.11			-0.00
			[0.13]			[0.17]
Announcement x Treatment (Speculative) x Branch			0.01			0.14***
			[0.05]			[0.04]
Implementation x Treatment (Speculative) x Branch			0.01			0.02
			[0.04]			[0.04]
Risky Treatment Controls	Y	Y	Y	Y	Y	Y
CRA Assessment Area Controls			Y			Y
Lender-Year-Quarter FE	Y	Y	Y	Y	Y	Y
County-Year-Quarter FE	Y	Y	Y	Y	Y	Y
Lender-County FE	Y	Y	Y	Y	Y	Y
Sample	All lenders	All lenders	Banks	All lenders	All lenders	Banks
Observations	108,292	103,893	42,412	117,713	113,217	45,396
R-squared	0.78	0.78	0.79	0.83	0.83	0.83

Table 11. Spillover Effects onto Small Business Lending

This table presents OLS regression results at the county-lender-year level where the natural log of small business lending dollar amounts are regressed onto the pre policy lender-county-level policy exposure. Treatment (Speculative) equals one if the lender-county cell's 2020 speculative home purchase and refinance loan amount sold to the GSEs divided by its total conventional conforming home purchase and refinance mortgage sold to the GSEs in 2020 is greater than 7% and zero otherwise. Treatment (Risky Purchase) and Treatment (Risky Refi) are defined in the same manner and included as control variables. Post equals one for 2021 and zero for 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 source: CRA and CHMDA.

	Ln(Small Business Loan Volume)		
	(1)	(2)	(3)
Post x Treatment (Speculative)	-0.102***	-0.044**	-0.048**
	[0.018]	[0.021]	[0.021]
Branch		0.975***	0.860***
		[0.217]	[0.127]
Post x Branch		-0.336***	-0.359***
		[0.042]	[0.047]
Branch x Treatment (Speculative)		-0.192	-0.100
		[0.175]	[0.135]
Post x Branch x Treatment (Speculative)		0.015	0.011
		[0.033]	[0.035]
Risky Treatment Controls	Y	Y	Y
CRA Assessment Area Controls			Y
Lender-Year-Quarter FE	Y	Y	Y
County-Year-Quarter FE	Y	Y	Y
Lender-County FE	Y	Y	Y
Observations	108,978	108,978	108,978
R-squared	0.935	0.936	0.937

Table 12. GSE Purchase Cap and Housing Transactions

This table presents OLS regression results where measures of housing market transactions are regressed onto GSE purchase cap policy treatment intensity variables. Each observation is a census tract by year-quarter cell. The outcome variables for Panel A are as follows. Column 1: the percentage of mortgaged non-corporate non-primary-residence transactions. Column 2: the percentage of cash non-corporate non-primary-residence transactions. Column 3: the percentage of non-corporate primary-residence transactions. Column 4: the percentage of corporate transactions. Panel B reports the results for the number of transactions. Treatment Intensity is calculated as, for 2020, the tract's total amount of conventional speculative home purchase and refinance loans sold to the GSEs divided by the tract's total amount of conventional home purchase and refinance loans sold to the GSEs. Treatment Intensity (Risky Purchase) and Treatment Intensity (Risky Refi) are defined in a similar manner and included as control variables but not reported. Announcement equals one for 2021Q1 and zero otherwise. Implementation equals one for 2021Q2 and 2021Q3 and zero otherwise. County-level COVID-19 controls include the total number of COVID-19 cases and deaths in each quarter. Heteroskedasticity-robust standard errors are clustered at the tract level. *, **, and *** denote 10%, 5%, and 1% statistical significance levels, respectively. Data source: CHMDA and CoreLogic.

Panel A: % Transactions

	% Speculative Mortgaged Transactions	% Speculative Cash Transactions	% Primary Residence Transactions	% Corporate Transactions
	(1)	(2)	(3)	(4)
Announcement x Treatment Intensity	-0.012**	-0.005	0.009	0.006
	[0.006]	[0.005]	[0.007]	[0.006]
Implementation x Treatment Intensity	-0.038***	0.003	0.012**	0.018***
	[0.004]	[0.004]	[0.005]	[0.005]
County COVID-19 Controls	Y	Y	Y	Y
Risky Treatment Controls	Y	Y	Y	Y
Year-Quarter FE	Y	Y	Y	Y
Tract FE	Y	Y	Y	Y
Observations	324,433	324,433	324,433	324,433
R-squared	0.738	0.476	0.756	0.493

Panel B: # Transactions

	# Speculative Mortgaged Transactions	# Speculative Cash Transactions	# Primary Residence Transactions	# Corporate Transactions
	(1)	(2)	(3)	(4)
Announcement x Treatment Intensity	0.062	0.027	1.426***	0.458***
	[0.067]	[0.041]	[0.137]	[0.054]
Implementation x Treatment Intensity	-0.669***	-0.018	1.138***	0.270***
	[0.058]	[0.034]	[0.095]	[0.042]
County COVID-19 Controls	Y	Y	Y	Y
Risky Treatment Controls	Y	Y	Y	Y
Year-Quarter FE	Y	Y	Y	Y
Tract FE	Y	Y	Y	Y
Observations	324,433	324,433	324,433	324,433
R-squared	0.835	0.715	0.904	0.690

Table 13. GSE Purchase Cap and House Prices

This table presents OLS regression results where measures of house price growth are regressed onto GSE purchase cap policy treatment intensity variables. Each observation is a census tract by year-quarter cell. The outcome variable for column 1 is the growth rate of average house price in the tract and year-quarter. The outcome variable for column 2 is the growth rate of median house price in the tract and year-quarter. Treatment Intensity is calculated as, for 2020, the tract's total amount of speculative home purchase and refinance loans sold to the GSEs divided by the tract's total amount of conventional conforming home purchase and refinance loan sold to the GSEs. Treatment Intensity (Risky Purchase) and Treatment Intensity (Risky Refi) are defined in a similar manner and included as control variables but not reported. Announcement equals one for 2021Q1 and zero otherwise. Implementation equals one for 2021Q2 and 2021Q3 and zero otherwise. County-level COVID-19 controls include the total number of COVID-19 cases and deaths in each quarter. Heteroskedasticity-robust standard errors are clustered at the tract level. *, **, and *** denote 10%, 5%, and 1% statistical significance levels, respectively. Data source: CHMDA and CoreLogic.

	House Price Growth (Average)	House Price Growth (Median)
	(1)	(2)
Announcement x Treatment Intensity	-0.064***	-0.064***
	[0.014]	[0.013]
Implementation x Treatment Intensity	-0.032***	-0.020**
	[0.008]	[0.008]
County COVID-19 Controls	Y	Y
Risky Treatment Controls	Y	Y
Year-Quarter FE	Y	Y
Tract FE	Y	Y
Observations	317,598	317,598
R-squared	0.066	0.069

Table 14. GSE Purchase Cap and Real Effects

This table presents OLS regression results where measures of local economic outcomes are regressed onto GSE purchase cap policy exposure. Each observation is a county and year-quarter cell. Columns 1 and 2 report the results for the growth rate of one-unit single-family house building permits. Columns 3 through 6 report the results for the growth rate of residential construction employment and wage. Treatment Intensity is calculated as, for 2020, the county's total amount of speculative home purchase and refinance loans sold to the GSEs divided by the county's total amount of conventional conforming home purchase and refinance loans sold to the GSEs. Treatment Intensity (Risky Purchase) and Treatment Intensity (Risky Refi) are defined in a similar manner and included as control variables but not reported. Announcement equals one for 2021Q1 and zero otherwise. Implementation equals one for 2021Q2 and 2021Q3 and zero otherwise. 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 source: CHMDA, Census Building Permit Survey, and Bureau of Labor Statistics Quarterly Census of Employment and Wages.

	One-Unit Permit Growth		Construction Employment Growth		Average Construction Wage Growth	
	(1)	(2)	(3)	(4)	(5)	(6)
Announcement x Treatment Intensity	-0.12	-0.11	0.07	0.10	0.17	0.21*
	[0.21]	[0.21]	[0.11]	[0.12]	[0.12]	[0.12]
Implementation x Treatment Intensity	0.14	0.14	-0.03	0.01	0.03	0.07
	[0.20]	[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)		-1.24		1.11***		1.26***
		[1.13]		[0.34]		[0.35]
Risky Treatment Controls	Y	Y	Y	Y	Y	Y
Year-Quarter FE	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y
Observations	3,569	3,569	14,596	14,596	14,596	14,596
R-squared	0.11	0.11	0.07	0.07	0.06	0.06

Internet Appendix

Loan-Level Control Variable Definition (CHMDA)

This section describes and defines the control variables used in regressions results presented in Tables 2 through 7. 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. The loan purpose (home purchase or refinance) indicator variable is interacted with each loan characteristic indicator variable to allow for differences in lending standard across the two products.

Regression results presented in Tables 7, IA.2, IA.3, and IA.4 do not include CLTV, DTI, and credit score indicator variables because these loan characteristics are included in the regressions as continuous variables and interacted with loan type treatment indicator variables.

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. This set of indicator variables is only included in adverse selection regressions (Tables 3, IA.2, IA.3, and IA.4).

Non-Bank – Equals one if, for the data year, the Avery file indicates that the lender is of TYPE 40 or 41 and zero otherwise. Non-Bank is set to missing for TYPE = 11-14, 21-14, and 32-33.

Lender-Level Regression Control Variable Definition

This section defines control variables used in lender-level regression results presented in Tables 8 and 9.

Treatment (Risky Purchase) – Equals to one if the proportion of the lender's 2020 conventional risky home purchase loan amount sold to the GSEs relative to its total conventional home purchase and refinance mortgage sold to the GSEs in 2020 is greater than 6% and zero otherwise. This variable is separately interacted with Announcement and Implementation indicator variables.

Treatment (Risky Refi) – Equals to one if the proportion of the lender's 2020 conventional risky refinance loan amount sold to the GSEs relative to its total conventional home purchase and refinance mortgage sold to the GSEs in 2020 is greater than 3% and zero otherwise. This variable is separately interacted with Announcement and Implementation indicator variables.

Non-Bank – Equals one if, for the data year, the Avery file indicates that the lender is of TYPE 40 or 41 and zero otherwise. Non-Bank is set to missing for TYPE = 11-14, 21-14, and 32-33.

Within-Lender Regression Control Variable Definition

This section defines control variables used in within-lender regression results presented in Tables 10 and 11.

Treatment (Risky Purchase) – Equals to one if the proportion of the lender-county cell's 2020 risky home purchase loan amount sold to the GSEs relative to its total conventional conforming home purchase and refinance mortgage sold to the GSEs in 2020 is greater than 6% and zero otherwise. This variable is separately interacted with Announcement and Implementation indicator variables.

Treatment (Risky Refi) – Equals to one if the proportion of the lender-county cell's 2020 risky refinance loan amount sold to the GSEs relative to its total conventional conforming home purchase and refinance mortgage sold to the GSEs in 2020 is greater than 3% and zero otherwise. This variable is separately interacted with Announcement and Implementation indicator variables.

Branch – An indicator variable that equals one if a bank has branch presence in that county-year cell, based on the FDIC's Summary of Deposits data.

CRA Assessment Area – An indicator variable that equals one if a county is a CRA assessment area in each year, based on the Community Reinvestment Act data provided by the FFIEC.

Bank – Equals one when Non-Bank equals zero. Bank is set to missing for TYPE = 11-14, 21-14, and 32-33 in the Avery file.

Housing Market Variable Definition

This section defines control variables used in tract-level housing market regression results presented in Tables 12 and 13.

House Price Growth (Average) – 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 time periods (denominator).

House Price Growth (Median) – 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 time periods (denominator).

Treatment Intensity (Risky Purchase) – For 2020, the tract's total amount of risky home purchase loan sold to the GSEs divided by the tract's total amount of conventional conforming home purchase and refinance loan sold to the GSEs. This variable is separately interacted with Announcement and Implementation indicator variables.

Treatment Intensity (Risky Refi) – For 2020, the tract's total amount of risky refinance loan sold to the GSEs divided by the tract's total amount of conventional conforming home purchase and refinance loan sold to the GSEs. This variable is separately interacted with Announcement and Implementation indicator variables.

% Mortgaged Speculative Transactions – The percentage of mortgaged transactions associated with second/investment home in a given tract and year-quarter.

% Cash Speculative Transactions – The percentage of cash transactions associated with second/investment home in a given tract and year-quarter.

% Primary Residence 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.

 # Mortgaged Speculative Transactions – The number of mortgaged transactions associated with second/investment home in a given tract and year-quarter.

 # Cash Speculative Transactions – The number of cash transactions associated with second/investment home in a given tract and year-quarter.

 # Primary Residence 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.

Real Effects Variable Definition

This section defines control variables used in county-level real effects regression results presented in Table 14.

Treatment Intensity (Risky Purchase) – For 2020, the county's total amount of risky home purchase loan sold to the GSEs divided by the county's total amount of conventional conforming home purchase and refinance loan sold to the GSEs. This variable is separately interacted with Announcement and Implementation indicator variables.

Treatment Intensity (Risky Refi) – For 2020, the county's total amount of risky refinance loan sold to the GSEs divided by the county's total amount of conventional conforming home purchase and refinance loan sold to the GSEs. This variable is separately interacted with Announcement and Implementation indicator variables.

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 time 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 time 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 time 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.

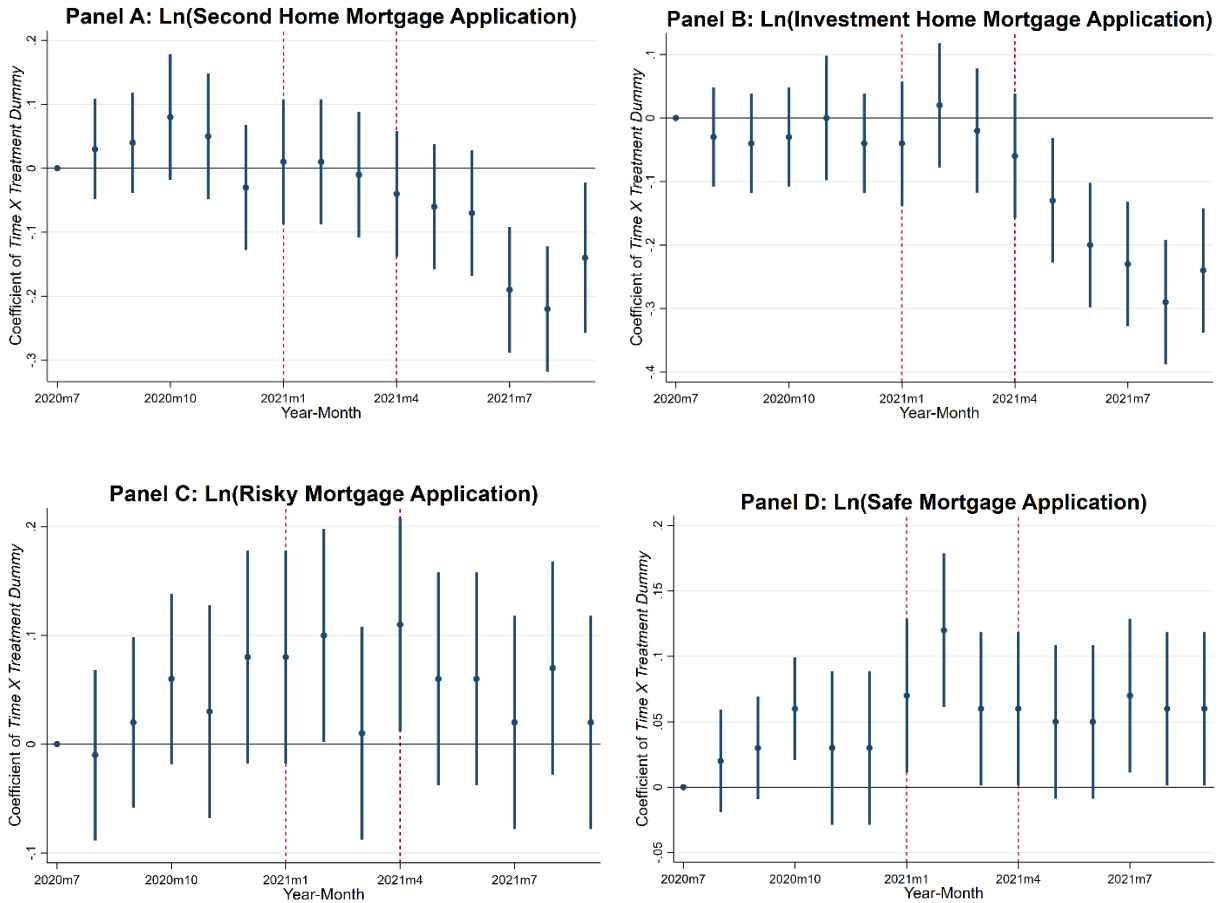**Ln(Per Capita Income)** – The natural logarithm of the county level per capita income in a given year.

Figure IA.1. Parallel Trends for Lender-Level Mortgage Application Volume

Panel A plots regression coefficients and their 95% confidence intervals from a lender-by-year-month-level OLS regression where the natural log of conventional conforming home purchase and refinance second home mortgage application volume in dollars is regressed onto year-month indicator variables interacted with the lender-level GSE purchase cap policy treatment indicator variable that equals one if the proportion of the lender's 2020 speculative home purchase and refinance loan amount sold to the GSEs relative to its total conventional conforming home purchase and refinance loan volume sold to the GSEs in 2020 is greater than 7% and zero otherwise. Treatment (Risky Purchase) and Treatment (Risky Refi) are defined in a similar manner and are interested with year-month indicator variable interaction terms and included as control variables. Year-month and lender fixed effects are included. Heteroskedasticity-robust standard errors are clustered at the lender level. The vertical dotted lines mark the month in which the GSE purchase cap policy was announced and implemented, respectively. Panel B, C, and D present the plots for investment home, risky, and safe mortgages, respectively. Data source: CHMDA.

Figure IA.2. Parallel Trends for Lender-Level Mortgage Origination Volume

Panel A plots regression coefficients and their 95% confidence intervals from a lender-by-year-month-level OLS regression where the natural log of conventional conforming home purchase and refinance second home mortgage origination volume in dollars is regressed onto year-month indicator variables interacted with the lender-level GSE purchase cap policy treatment indicator variable that equals one if the proportion of the lender's 2020 speculative home purchase and refinance loan amount sold to the GSEs relative to its total conventional conforming home purchase and refinance loan volume sold to the GSEs in 2020 is greater than 7% and zero otherwise. Treatment (Risky Purchase) and Treatment (Risky Refi) are defined in a similar manner and are interested with year-month indicator variable interaction terms and included as control variables. Year-month and lender fixed effects are included. Heteroskedasticity-robust standard errors are clustered at the lender level. The vertical dotted lines mark the month in which the GSE purchase cap policy was announced and implemented, respectively. Panel B, C, and D present the plots for investment home, risky, and safe mortgages, respectively. Data source: CHMDA.
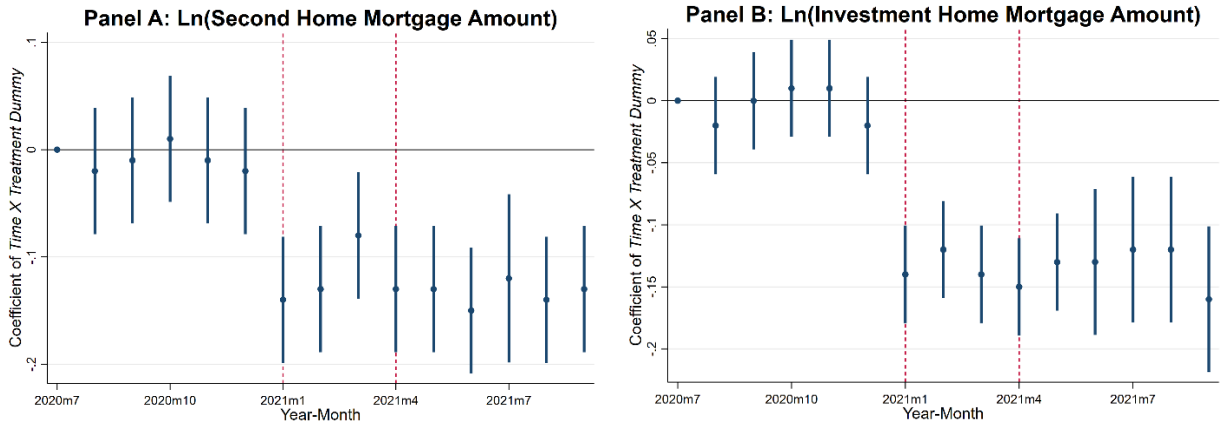
Figure IA.3. Parallel Trends for Lender-County-Level Mortgage Origination

Panel A plots regression coefficients and their 95% confidence intervals from a lender-county-year-month-level OLS regression where the natural log of conventional conforming home purchase and refinance second home mortgage origination volume in dollars is regressed onto year-month indicator variables interacted with the lender-county-level GSE purchase cap policy speculative mortgage treatment intensity variable. Risky mortgage (home purchase and refinance, separately) treatment intensity variables are interacted with year-month indicator variables and are included as control variables. Lender by year-month, county by year-month, and lender by county fixed effects are included. Heteroskedasticity-robust standard errors are clustered at the lender level. Panel B presents the results for investment home mortgages. The vertical dotted line marks the month in which the GSE purchase cap policy was announced and implemented. Data source: CHMDA.
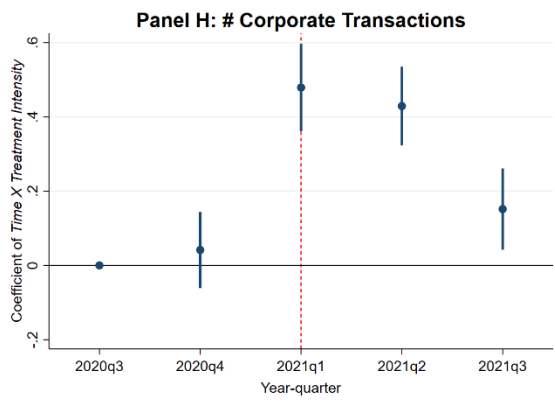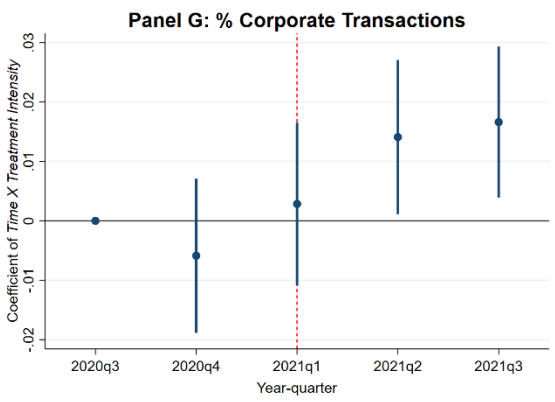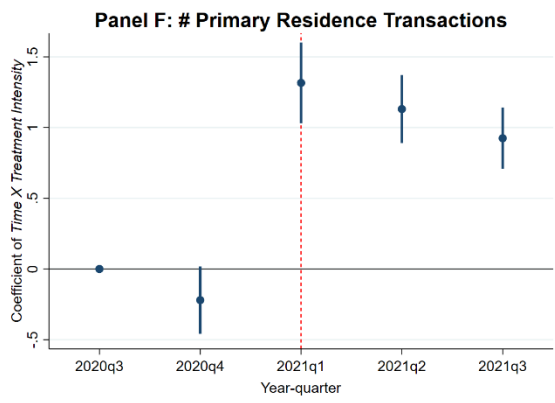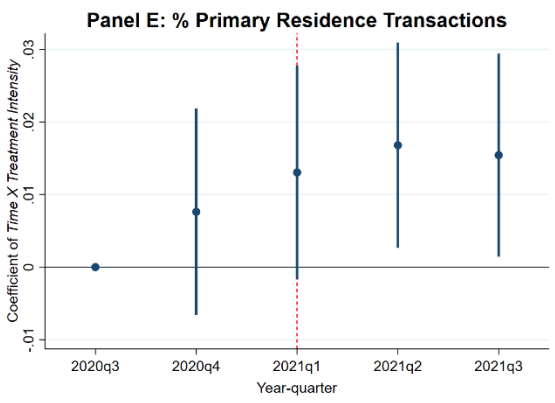
Panel A: % Mortgaged Speculative Transactions

Panel B: # Mortgaged Speculative Transactions

Panel C: % Cash Speculative Transactions

Panel D: # Cash Speculative Transactions

Panel E: % Primary Residence Transactions

Panel F: # Primary Residence Transactions

Panel G: % Corporate Transactions

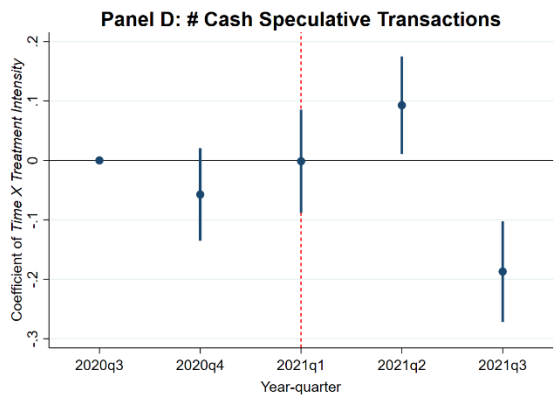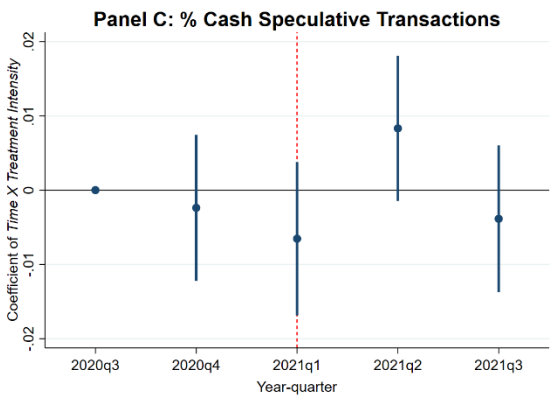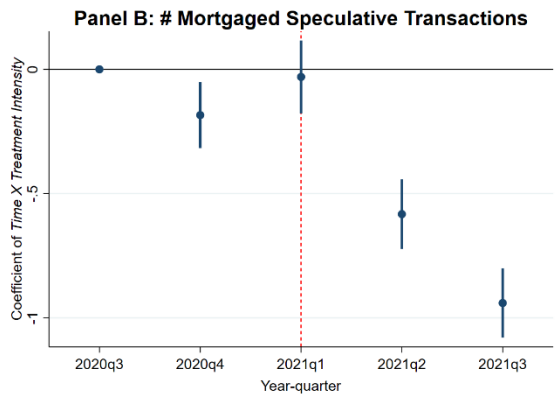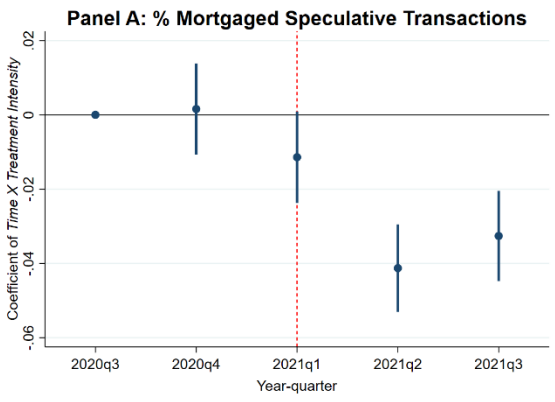**Panel H: # Corporate Transactions**

Figure IA.4. Parallel Trends for Housing Transactions

Figure IA.4 plots regression coefficients and their 95% confidence intervals from a tract-quarter-level OLS regression where the percentage and the number of mortgaged speculative, cash speculative, primary residence, and corporate transactions of single-family houses are separately regressed onto year-quarter indicator variables interacted with the tract-level GSE purchase cap treatment intensity variable. The outcome variables are defined as described in Table 14. Treatment intensity is a measure of each tract's exposure to the policy. The regression specification includes risky mortgage treatment intensity controls, county-level COVID-19 controls, tract fixed effects, and year-quarter fixed effects. The vertical dotted line marks the quarter in which the GSE purchase cap policy was announced. Heteroskedasticity-robust standard errors are clustered at the tract level. Data source: CoreLogic.
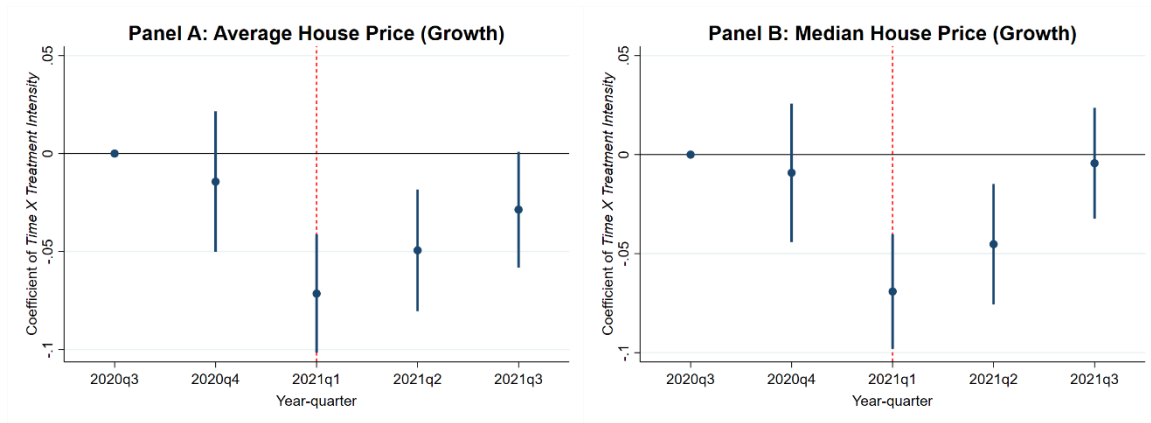
Figure IA.5. Parallel Trends for House Price

Figure IA.5 plots regression coefficients and their 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 treatment intensity variable. The outcome variables are defined as described in Table 15. The regression specification includes risky mortgage treatment intensity controls, county-level COVID-19 controls, tract fixed effects, and year-quarter fixed effects. The vertical dotted line marks the quarter in which the GSE purchase cap policy was announced. Heteroskedasticity-robust standard errors are clustered at the tract level. Data source: CoreLogic.

Table IA.1. Summary Statistics of Loan-Level Control Variables

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

	Mean	Median	S.D.	N
	(1)	(2)	(3)	(4)
Application characteristics				
Applicant Age	44.52	42	13.85	6,805,319
Female	0.59	1	0.49	6,805,482
Unknown Sex	0.08	0	0.27	6,805,482
Both Sexes	0	0	0.03	6,805,482
Hispanic	0.11	0	0.31	6,805,482
Unknown Ethnicity	0.16	0	0.37	6,805,482
Asian	0.1	0	0.3	6,805,482
Black	0.05	0	0.21	6,805,482
Other Minority	0.01	0	0.1	6,805,482
Unknown Racce	0.17	0	0.37	6,805,482
Co-Applicant Indicator	0.42	0	0.49	6,805,482
Applicant Credit Score	758.53	768	41.98	6,794,163
Co-Applicant Credit Score	765.24	776	40.98	1,035,311
CLTV (%)	74.87	78.98	16.82	6,762,873
DTI (%)	33.99	34.88	9.7	6,782,478
Income (USD Thousands)	118.52	99	77.19	6,739,442
Loan Amount (USD Thousands)	305.57	278.91	149.92	6,805,480
AUS Approved	0.97	1	0.18	6,805,482
Home Purchase Mortgage	0.51	1	0.5	6,805,482

Table IA.2. GSE Purchase Cap, Loan Risk, and Risky Mortgage GSE Sale Probability

This table presents loan-level OLS regression results where the GSE sale indicator variable is regressed onto GSE purchase cap policy shock indicator variables. The outcome variable equals 100 if the mortgage was sold to Fannie Mae or Freddie Mac by the end of the reporting calendar year and zero otherwise. Risky equals one for risky mortgages associated with primary residences 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 divided by 100. 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 and refinance 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 source: CHMDA.

	GSE Sale	
	(1)	(2)
Risky	-16.83***	-7.98**
	[3.55]	[3.72]
Risky x Announcement	-1.33	-14.99***
	[5.13]	[5.17]
Risky x Implementation	4.97	-1.52
	[4.80]	[4.10]
Risky x Credit Score	1.77*	0.19
	[0.96]	[1.08]
Risky x Announcement x Credit Score	0.59	1.90**
	[1.04]	[0.83]
Risky x Implementation x Credit Score	2.03**	2.29**
	[0.95]	[0.96]
Risky x CLTV	1.15	4.91
	[3.92]	[4.21]
Risky x Announcement x CLTV	-3.07	-3.77
	[3.39]	[2.90]
Risky x Implementation x CLTV	-18.01***	-13.63***
	[4.39]	[4.09]
Risky x DTI	8.54	6.86
	[7.11]	[7.70]
Risky x Announcement x DTI	1.20	10.21*
	[4.78]	[5.49]
Risky x Implementation x DTI	-7.63	-5.49
	[6.54]	[5.97]
Controls x Loan Purpose FE	Y	Y
Tract FE	Y	Y
Lender x Year-Quarter FE	Y	Y
LLPA x Year-Quarter FE		Y
Observations	6,029,860	6,029,860
R-squared	0.61	0.61

Table IA.3. GSE Purchase Cap, Loan Risk, and Second Home Mortgage GSE Sale Probability

This table presents loan-level OLS regression results where the GSE sale indicator variable is regressed onto GSE purchase cap policy shock indicator variables. The outcome variable equals 100 if the mortgage was sold to Fannie Mae or Freddie Mac by the end of the reporting calendar year and zero otherwise. Second equals one for mortgages associated with second 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 divided by 100. 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 and refinance 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 source: CHMDA.

	GSE Sale	
	(1)	(2)
Second	-7.12***	-1.85
	[2.32]	[2.35]
Second x Announcement	6.60*	-0.82
	[3.61]	[3.67]
Second x Implementation	8.31*	2.88
	[4.75]	[5.14]
Second x Credit Score	0.44*	0.04
	[0.26]	[0.27]
Second x Announcement x Credit Score	-0.93**	-0.07
	[0.46]	[0.45]
Second x Implementation x Credit Score	-1.99***	-1.50**
	[0.67]	[0.68]
Second x CLTV	5.45***	2.18***
	[0.94]	[0.77]
Second x Announcement x CLTV	-0.53	0.68
	[1.41]	[1.39]
Second x Implementation x CLTV	-3.96**	-1.64
	[1.91]	[1.99]
Second x DTI	1.20	1.10
	[1.09]	[1.08]
Second x Announcement x DTI	1.50	1.62
	[1.43]	[1.43]
Second x Implementation x DTI	3.07	3.04
	[2.27]	[2.25]
Controls x Loan Purpose FE	Y	Y
Tract FE	Y	Y
Lender x Year-Quarter FE	Y	Y
LLPA x Year-Quarter FE		Y
Observations	6,084,868	6,084,864
R-squared	0.61	0.61

Table IA.4. GSE Purchase Cap, Loan Risk, and Investment Home Mortgage GSE Sale Probability

This table presents loan-level OLS regression results where the GSE sale indicator variable is regressed onto GSE purchase cap policy shock indicator variables. The outcome variable equals 100 if the mortgage was sold to Fannie Mae or Freddie Mac by the end of the reporting calendar year and zero otherwise. Investment equals one for mortgages associated with 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 divided by 100. 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 and refinance 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 source: CHMDA.

	GSE Sale	
	(1)	(2)
Investment	-3.13	2.02
	[3.33]	[3.28]
Investment x Announcement	1.33	-5.81
	[5.39]	[5.50]
Investment x Implementation	8.78	1.02
	[7.89]	[8.84]
Investment x Credit Score	0.32	-0.03
	[0.48]	[0.47]
Investment x Announcement x Credit Score	-1.07	-0.32
	[0.72]	[0.71]
Investment x Implementation x Credit Score	-5.17***	-4.51***
	[1.02]	[1.07]
Investment x CLTV	4.40**	0.27
	[2.20]	[2.04]
Investment x Announcement x CLTV	3.02	5.13**
	[2.65]	[2.52]
Investment x Implementation x CLTV	-2.15	2.16
	[6.18]	[6.36]
Investment x DTI	-4.58***	-4.47***
	[1.60]	[1.61]
Investment x Announcement x DTI	0.42	0.57
	[3.17]	[3.17]
Investment x Implementation x DTI	-1.01	-0.95
	[5.44]	[5.41]
Controls x Loan Purpose FE	Y	Y
Tract FE	Y	Y
Lender x Year-Quarter FE	Y	Y
LLPA x Year-Quarter FE		Y
Observations	6,202,717	6,202,712
R-squared	0.60	0.60