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Evidence from the COVID-19 Pandemic

Andreas Fuster
École Polytechnique Fédérale de Lausanne

Aurel Hizmo
Independent

Lauren Lambie-Hanson
Federal Reserve Bank of Philadelphia Consumer Finance Institute

James Vickery
Federal Reserve Bank of Philadelphia

Paul Willen
Federal Reserve Bank of Boston and NBER

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How Resilient Is Mortgage Credit Supply? Evidence from the COVID-19 Pandemic*

Andreas Fuster Aurel Hizmo Lauren Lambie-Hanson
James Vickery Paul Willen

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Abstract

We study the resilience of US mortgage credit supply during the COVID-19 pandemic—the most significant shock since the financial crisis—and draw out broader lessons about the functioning of this important market. While mortgage lending boomed in 2020 and 2021, we find that a sharp increase in intermediation markups limited the pass-through of low rates to households. We link this increase in markups to capacity constraints amplified by pandemic-related operational and labor market frictions. We also present new evidence that capacity constraints in the mortgage market are national in scope and have not yet been significantly mitigated by recent technological change. Nonbank lenders, often thought to be fragile, gained market share from banks but remain reliant on securitization. We also find evidence that government credit guarantees support the flow of credit to risky borrowers but are not always sufficient, and that quantitative easing particularly boosts credit supply for the specific types of loans being purchased.

Keywords: mortgage, credit, financial intermediation, nonbanks, fintech, COVID-19.
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I Introduction

The pandemic years 2020 and 2021 were an extraordinary period for the US mortgage market. In both years, lenders underwrote over $4 trillion in new mortgages, far higher than in any other year except 2003.[1] Rates on 30-year fixed-rate mortgages (FRMs) fell to historic lows below 3% for an extended period. At the same time, however, the pandemic was of course also a large negative economic shock with effects on borrower default risk and financial markets more broadly, and virus-related restrictions complicated many activities including housing transactions and the origination of mortgages.

We use this period to study the resilience of US mortgage credit supply, focusing on broader lessons for understanding the functioning of this critical market. One key goal is to shed light on the effects of well-documented structural changes in the mortgage market since the 2007-09 global financial crisis (GFC), including a secular shift in lending to less-regulated nonbanks (Buchak et al., 2018; Kim et al., 2022), the diffusion of online lending (Buchak et al., 2018; Fuster et al., 2019) and changes in regulation and the role of government. These developments raise many questions: How resilient are the new nonbank lenders in periods of stress? Has new technology alleviated lender capacity constraints, making credit supply more elastic? How sensitive are mortgage risk premia to economic and financial shocks, and what role do government guarantees and other interventions (e.g., quantitative easing, or QE) play in mitigating these effects?

We start by documenting that, even though mortgage rates reached record lows in 2020-21, the gap between mortgage rates and 10-year Treasury yields in fact reached peak levels not seen since the GFC—see Figure 1.[2] However, the cause of this increase in the mortgage-Treasury spread was different from the GFC (and from the recent 2022-24 pe-

[1]From 2008 through 2019, annual mortgage originations never exceeded $2.4 trillion, and they exceeded $2 trillion only three times. Lending volume was $3.7 trillion in 2003. Statistics are from *Inside Mortgage Finance* and can be seen on p. 8 of Urban Institute (2024).

[2]The effective duration of a 30-year mortgage is much shorter than 30 years due to prepayment. Ten-year Treasury yields are therefore widely used as a benchmark for mortgage rates, even though this benchmark is imperfect, for reasons we explain below.

riod when this spread also widened significantly): it is fully explained by a large rise in the "primary-secondary spread," a measure of mortgage lenders' markups.[3] Another, conceptually sounder measure of markups, "gain-on-sale," also increased sharply early in the pandemic and stayed elevated through to late 2021.

Intermediation markups typically rise during refinancing booms due to lender capacity constraints (Fuster et al., 2024). But this historical relationship accounts for less than half of the increase in 2020-21. In other words, the elasticity of mortgage supply was abnormally *low*, despite the recent widespread adoption of online and digital technologies to streamline lending. We find evidence that operational and labor market frictions related to the pandemic can account for heightened capacity constraints in 2020-21—e.g., licensing of new loan officers was disrupted, contributing to high labor utilization and wages for existing workers. Perhaps surprisingly, we also find little evidence that fintech lenders expanded supply more elastically than other nonbanks, further indicating that technology has not yet "solved" the problem of capacity constraints.

We also present novel evidence on the nature of capacity constraints in the mortgage market, concluding that these constraints today are effectively national in scope because the US mortgage market is highly integrated geographically. Specifically we show that most mortgages are originated by lenders that operate in many regions, and that lenders, and even individual loan officers, expanded to new markets in 2020-21 to offset local differences in demand. As a result, there is little or no cross-sectional relationship between local demand shocks (or other local factors) and mortgage rates or origination timelines, even though these variables are tightly connected in the time series.

We then consider other potential drivers of high intermediation markups in 2020-21. First, we study in detail the role of financial constraints facing nonbank lenders, a group often considered to be financially fragile. Studying the first major shock since the rise of nonbanks in the 2010s, we in fact find that nonbanks expanded lending *more* elasti-

[3] We use the term "markup" throughout as shorthand for "gross markup" or "gross margin," meaning in our case the difference between the marginal revenue of an intermediary and the marginal direct cost of funds lent to the borrower (but without accounting for wages, overhead, etc.), as in, e.g., Anderson et al. (2018).

cally than banks, aside from a brief period at the start of the pandemic. Further, even this initial drop in lending is more connected to lenders' dependence on third-party originations (e.g., brokers) rather than capital or liquidity constraints. Nonbank lending fell more persistently in the jumbo market, however, reflecting the reliance of nonbanks on government-sponsored securitization.

Using variation across borrower types and locations, we are also able to rule out several other plausible explanations for high markups in the conventional conforming market (the main focus of our analysis[4]), including forbearance and default risk and the direct macroeconomic and health effects of the virus. High markups could also reflect a rise in lender market power, perhaps due to limited shopping by borrowers. We find little support for this channel, however: borrowers, if anything, searched more actively than usual during the pandemic, local market concentration decreased after the boom began, and changes in mortgage rates were not closely connected to local concentration.

Finally, we extend our analysis beyond conventional conforming mortgages to explore credit supply dynamics in two other segments—the jumbo and Federal Housing Administration (FHA) markets. The jumbo market is informative because it lacks government guarantees and was not directly impacted by the Fed's mortgage purchases under QE. This, and the fact that QE did not target "superconforming" mortgages for institutional reasons, allows us to isolate the distinct roles of guarantees and QE in supporting credit conditions, and we find that both played a role. However, we also find that these interventions were insufficient to fully stabilize the FHA market, where credit availability declined relative to the prime conforming market, particularly for the riskiest borrowers. We argue that these effects stem at least in part from the fact that FHA loans are riskier for lenders and servicers compared to conventional loans (Kim et al., 2018).

We draw out several broader lessons from our results. (i) Despite recent technologi-

[4]"Conventional" refers to mortgages not directly insured by the government (e.g., by the Federal Housing Administration or the Department of Veterans Affairs). Mortgages that are insured by the government-sponsored enterprises Fannie Mae and Freddie Mac are "conventional conforming" while conventional *non*conforming loans include in particular "jumbo" loans with balances above the conforming loan limit.

cal advances, the US mortgage market still faces capacity constraints in periods of peak demand, suggesting there are bottlenecks that technology has not yet been able to effectively address. (ii) Today, capacity constraints are primarily national in scope, because the US mortgage market is geographically integrated, thus the key constraint on lending is *aggregate* industry resources. (iii) Nonbank mortgage lending may be more robust than previously appreciated, but remains dependent on government-sponsored securitization. (iv) Government guarantees support credit supply to riskier borrowers in the face of economic shocks, although, at least in the FHA market, these guarantees are not always sufficient to fully insulate borrowers. (v) QE has "local" effects on mortgage supply; even *within* the conforming market, QE particularly boosts supply in the segment where purchases are concentrated.

Our evidence contributes to a large body of research about the transmission of monetary policy and interest rate shocks through the mortgage market and the role of financial frictions, including Di Maggio et al. (2017), Berger et al. (2021) and Drechsler et al. (2024); see Amromin et al. (2020) for a review. Fuster et al. (2013, 2024), Sharpe and Sherlund (2016), Choi et al. (2022), and Frazier and Goodstein (2023) study how lender capacity constraints drive markups and lending during periods of high demand; we present new evidence that these constraints are national in scope and have not yet been alleviated through technology. We also contribute to research on mortgage QE (Krishnamurthy and Vissing-Jorgensen, 2011; Di Maggio et al., 2020) using novel variation in the intensity of Fed purchases within the conforming market, and provide new evidence on the effects of government guarantees on credit supply in times of stress, finding that guarantees support lending but are sometimes insufficient (see Calem et al., 2013; Vickery and Wright, 2013; Hurst et al., 2016, for related work studying earlier periods).

We also extend the literature studying the effects of post-GFC changes to the US mortgage market—factors including tighter regulation and the rapid growth of nonbank and online lending (e.g., DeFusco et al., 2019; Gete and Reher, 2020; D'Acunto and Rossi, 2022). Research has identified several factors underlying the expansion of nonbanks and highlighted financial instability concerns associated with the nonbank business model (e.g., Buchak et al., 2018, 2024; Kim et al., 2018, 2022; Jiang, 2023). We find that nonbanks were resilient to the first major shock since their re-emergence in the 2010s, and in fact expanded lending more elastically than banks, except when liquid secondary markets were unavailable. We also present new evidence on the role of technology (see Buchak et al., 2018; Fuster et al., 2019; Jagtiani et al., 2021; Bartlett et al., 2022; Allen et al., 2023, for prior contributions), concluding that the rapid spread of online and digital lending has not yet eased industry capacity constraints, at least based on the experience of the 2020-21 boom.

Finally, we contribute to research about the mortgage market and consumer credit markets more generally during the COVID-19 pandemic (e.g., Bracke et al., 2020; Iverson et al., 2020; Cherry et al., 2021; Agarwal et al., 2023; Horvath et al., 2023) and to literature examining the role of technology for lending during this period (e.g., Ben-David et al., 2021; Kwan et al., 2021; Erel and Liebersohn, 2022; Branzoli et al., 2024).[5]

II Data

In this section, we provide an overview of the different data sources we use in this paper.

Optimal Blue. Optimal Blue is a platform allowing lenders to access pricing information, initiate rate locks, and sell mortgages.[6] Lenders are typically nonbank mortgage companies, but smaller banks and credit unions are also represented. Over 1,000 lenders and 200 investors use the platform, which is estimated to handle about one-third of US mortgage originations in recent years. We use two forms of information produced by the platform.

Rate locks. These data reflect individual mortgage locks processed by Optimal Blue,

[5] Of course, the onset of COVID-19 led to severe disruptions in financial markets, and various spreads widened (see, e.g., Haddad et al., 2021; He et al., 2022). Siani (2024) shows that the gap in yields on corporate bonds between the primary market (at issuance) and secondary market trading also increased during the pandemic, by about 20bp, perhaps due to limited risk-bearing capacity by intermediaries given that the corporate bond market, like the jumbo market, does not feature government credit guarantees.

[6] Optimal Blue data (as referenced throughout) is anonymized mortgage market/rates data that does not contain lender or customer identities or complete rate sheets.

covering around 280 metropolitan and rural areas. They include comprehensive underwriting variables and offer several advantages over servicing data: e.g., they include data on discount points and credits, the exact rate lock date (as opposed to closing date, which happens much later), and the lock duration.

Mortgage offers. Optimal Blue's "Pricing Insight" engine provides the real-time distribution of lender offers (combinations of rates and net points and fees) for a loan with given characteristics in a particular local market.[7] This tool is designed for lenders to compare their pricing with that of their peers. Mortgage offer rates represent a direct measure of supply that can be observed regardless of whether the offer results in a loan in equilibrium. The Insight data also allow us to see how the number of lenders active in different segments of the market evolved over the pandemic.

Home Mortgage Disclosure Act (HMDA) Data. We use the confidential HMDA data, which covers nearly all US mortgage applications (Bhutta et al., 2017). These data include a rich set of borrower and loan characteristics such as income, credit score, debt-to-income (DTI) ratio, loan-to-value (LTV) ratio, loan amount, property census tract, loan purpose (e.g., home purchase or refinance), and the exact application and closing date.

CSBS Nonbank Call Report and Consumer Access Data. We use quarterly data on the balance sheets of nonbank mortgage lenders from Mortgage Call Reports (MCR) to study the relationship between lending and nonbank characteristics.[8] To do this, we merge the MCR data with HMDA, matching on lender name. In total, we match 398 nonbanks accounting for 89% of total nonbank lending in the period from July 2019 to December 2020. We also obtain from the CSBS the Nationwide Multistate Licensing System (NMLS) Consumer Access data, which include the employment history of state-licensed and federally

[7] We have daily data in one local market (Los Angeles), twice-weekly data in four markets, and weekly data in 15 additional markets, collecting offer data for 100 loan types representing different combinations of FICO score, LTV ratio, loan program, purpose (purchase or cash-out refinance), occupancy, rate type (30-year fixed or 5/1 adjustable), and loan amount. For more details, see Bhutta et al. (2024), who compare mortgage offer rates and lock rates to study the efficiency of borrower search in the mortgage market.

[8] These data are available to Federal Reserve researchers through an agreement with the Conference of State Bank Supervisors (CSBS), which owns and operates the system that collects MCR data on behalf of state regulators. Similar data are used by Jiang et al. (2020) to study the capital structure of nonbanks.

registered mortgage loan officers, which we use to study loan officer licensing activity.

Other Data Sources. For mortgage rates, in addition to Optimal Blue, we use data from the Freddie Mac Primary Mortgage Market Survey (PMMS) and the Mortgage Bankers Association (MBA). Mortgage-backed securities (MBS) pricing information comes from J.P. Morgan Markets. Mortgage servicing rights valuation data are provided by SitusAMC, an independent valuation service company. For direct evidence on lender income, costs, and employment, we use the MBA Quarterly Performance Report. Data on mortgage industry job postings for loan officers come from Burning Glass Technologies. Data on county-level daily COVID-19 cases come from the *New York Times* GitHub repository, and data on mobility come from Opportunity Insights. Metro area population data are from the 2018 5-Year American Community Survey, and unemployment data are from the Bureau of Labor Statistics' Local Area Unemployment Statistics. Evidence on borrower search is obtained from Google Trends. Data on mortgage borrowers' experiences in the application process come from the National Survey of Mortgage Originations (NSMO) released by the Federal Housing Finance Agency. Lastly, we use ICE McDash servicing data ("McDash data") to study mortgage performance.

III Rates and Markups for Conforming Mortgages

In this section, we decompose the mortgage-Treasury spread from Figure 1 into different components and show that the increase in 2020-21 was entirely due to a sharp rise in the primary-secondary spread, a measure of the intermediation markup in the primary mortgage market. We then present alternative measures of this markup—including our preferred one, gain-on-sale—and show that they paint a similar picture.

III.A Decomposing the Mortgage-Treasury Spread

Define r_p as the mortgage rate paid by the borrower (in the "primary market"), r_{10} as the yield on a 10-year Treasury note, and r_s as the yield on a new-production MBS into which a typical newly originated mortgage with note rate r_p would be securitized (in the "secondary market"). We can decompose the mortgage-Treasury spread as:

$$r_p - r_{10} = \underbrace{r_p - r_s}_{\text{Primary-secondary spread}} + \underbrace{r_s - r_{10}}_{\text{MBS spread}} . \tag{1}$$

We can furthermore decompose the MBS spread as follows:

$$r_s - r_{10} \approx \underbrace{r_{\text{dur}} - r_{10}}_{\text{Duration Adjustment}} + \begin{matrix}\text{Option}\\ \text{Cost}\end{matrix} + \begin{matrix}\text{Option-Adjusted}\\ \text{Spread (OAS)}\end{matrix} . \tag{2}$$

Duration Adjustment reflects the fact that the MBS may have a different duration from the 10-year Treasury. MBS duration is not known ex-ante, since it depends on prepayment behavior, so instead it is estimated using a model that simulates different interest rate and prepayment paths. *Option Cost* measures the value of the borrower's prepayment option; the borrower can prepay at any time and will tend to do so especially when rates fall (in order to refinance into a new loan). Since MBS investors are short this option, they require compensation in terms of a higher MBS yield. Finally, *Option-Adjusted Spread* (OAS) is a residual that captures various factors that affect relative pricing between Treasuries and MBS, such as liquidity, relative bond supply, perceived credit risk differences, and non-interest-rate prepayment risk (Boyarchenko et al., 2019).[9]

III.A.1 Measurement

While mortgage rates and Treasury yields are readily available, computing the decompositions in equations (1) and (2) is less straightforward. Most important, MBS yield, duration, option cost, and OAS are not directly observed, but are obtained from MBS pricing models; we rely on models from J.P. Morgan Markets, as noted earlier. Two further complications are that (i) MBS are traded in 50 basis point (bp) coupon increments, and a mortgage with a given note rate could be securitized into different new production

[9] For textbook descriptions of MBS pricing, see Fabozzi (2016) or Davidson and Levin (2014). Note that the decomposition in (2) is not exact, since the OAS and the "zero-volatility spread" (the sum of OAS and option cost) are calculated as an average spread relative to each point on the interest rate curve based on which future cash flows are discounted, while the MBS spread is measured at a given point on that curve.

coupons; and (ii) MBS investors do not receive the entire note rate since some cash flows are diverted to pay for the agency credit guarantee (g-fees) and servicing. To account for these factors we calculate a net note rate:

$$\textit{Net Note Rate} = r_p - g - s. \tag{3}$$

For the guarantee fee g, we take the flow g-fee on new production MBS (as in Fuster et al., 2013); the (base) servicing fee s is set to 25bp, which is the market convention for MBS issued by the government-sponsored enterprises (GSEs) Fannie Mae and Freddie Mac. We then calculate the MBS yield, duration, option cost, and OAS by interpolating values between the two MBS coupons on either side of the net note rate.[10]

III.B Decomposing the Mortgage-Treasury Spread over 2020–21

Figure 2 traces out the evolution of the mortgage-Treasury spread in 2020-21 (normalized to zero at the start of 2020) and decomposes this evolution into the four components discussed above. The mortgage-Treasury spread (the black dashed line in the figure) increased rapidly starting in late February, peaking at about 90bp above pre-pandemic levels in late March. The spread then gradually normalized, but even in August remained about 50bp higher than at the start of the year. The spread returned to pre-pandemic levels by November 2020, and thereafter stayed below its level at the start of 2020.

The decomposition shows that, except for a brief period at the onset of the pandemic, the rise in the mortgage-Treasury spread in 2020 is *more* than entirely accounted for by a sharp increase in the primary-secondary spread—that is, by a higher markup in the primary mortgage market. In contrast, the three financial market components (duration adjustment, option cost, and OAS) were actually *lower* than their pre-pandemic levels over most of 2020-21. OAS did spike temporarily in March 2020, reflecting an amplification of risk premia in financial markets and deleveraging by mortgage REITs.[11] Option cost

[10]Our method estimates the MBS yield for new mortgage production, and differs from the commonly used "current coupon" (CC) MBS yield, which is the hypothetical coupon trading at par. The CC yield is not reliable in 2020 since every coupon traded far above par. See Fuster et al. (2013) for related discussion.

[11]While our measure of OAS is based on a pricing model from J.P. Morgan, Appendix Figure A.1 shows that

also increased, reflecting higher interest rate volatility. But these spikes were short-lived. On March 15, the Federal Reserve resumed its MBS quantitative easing program, and on March 23 announced it would purchase agency MBS in the volume needed to support market functioning. These actions led to a rapid normalization of OAS, which then fell below pre-pandemic levels. The duration adjustment also became negative after February 2020, reflecting a drop in the model-implied duration of newly originated mortgages (from 4.7 years in January 2020 to 3.2 years by July).

For comparison, Appendix Figure A.2 presents the same decomposition for two other episodes when the mortgage-Treasury spread was elevated: the 2007-09 financial crisis period and 2022-24 (featuring Fed rate hikes and "quantitative tightening"; see Drechsler et al., 2024). The figure shows that the primary-secondary spread did not play a key role in either of these episodes. During the financial crisis, the high spread was mainly due to higher OAS reflecting elevated risk premia, while in 2022-24 it was driven roughly equally by an increase in OAS, option cost (as rate volatility increased) and the duration adjustment, while the primary-secondary spread stayed flat.

Given these patterns, our focus will be on understanding the high primary-secondary spread, or more broadly high intermediation markups, during 2020-21.

III.C Alternative Measures of the Intermediation Markup

The primary-secondary spread is widely used to measure intermediation markups, but Fuster et al. (2013) and Fuster et al. (2024) argue that it is conceptually imperfect because it measures the instantaneous flow of income to intermediaries rather than the total gain reflecting the present value of these flows over the life of the mortgage. Due to prepayment, a mortgage has an uncertain and variable lifespan. Consequently, two loans with the same primary-secondary spread may have very different expected incomes and values depending on anticipated prepayment behavior. A second challenge is that measuring MBS yield requires a pricing model; the measure is therefore model-dependent.

OAS evolved very similarly when using Citi's pricing model.

A preferred measure of the markup is provided by "gain-on-sale," which takes the perspective of an intermediary selling the mortgage and the mortgage servicing right in the secondary market. Gain-on-sale is calculated as the present value of the net note rate (measured using secondary market MBS prices), plus the value of the servicing right (calculated using servicing multiples provided by SitusAMC), plus net points and fees. Details of our methodology are explained in Appendix A.1, where we also present a more formal treatment of the gain-on-sale calculation.

The top two panels of Figure 3 compare the primary-secondary spread and gain-on-sale over 2012-22. The two evolve similarly, and roughly double between the start of 2020 and mid-April, with gain-on-sale peaking at just over 500bp. The two measures stay at extremely elevated levels through most of the rest of 2020 before normalizing over the course of 2021. (For more details, see Appendix Figure A.3, which zooms in on the 2019-2021 period and also shows that these patterns are similar if we use alternative series for the primary mortgage rate.) By either measure, intermediation markups were much higher in 2020-21 than any other point in the sample period.

We can use gain-on-sale directly to get a sense of just how profitable mortgage lending was during this period. Focusing just on the last three quarters of 2020, originations averaged \$1.2 trillion a quarter; multiplying originations by our quarterly gain-on-sale measure implies total industry gain-on-sale of \$171 billion, or \$57 billion a quarter, compared to a quarterly average of only \$12 billion in 2019. This huge increase reflects the product of higher lending volume and higher margins. But even holding originations fixed, had gain-on-sale remained at its pre-pandemic level of 2.5%, the industry would have earned only \$88 billion from 2020:Q2 to 2020:Q4—about half as much as it did.

The bottom two panels of Figure 3 display measures of mortgage origination profit margins derived from SEC filings and MBA survey data. These measures have their limitations—e.g., they are average rather than marginal—but they tell a similar story, and suggest that mortgage lending was more profitable in 2020-21 than ever before or since.[12]

[12]For example, Rocket Companies, the largest US mortgage lender, recorded \$9.4bn in net income in 2020,

IV Capacity Constraints

In this section, we present evidence that capacity constraints amplified by pandemic-era operational and labor market frictions provide a coherent explanation for the strikingly high intermediation markups observed in 2020-21.

We start by showing that high markups are partially but not fully explained by the high level of mortgage demand—-in other words, credit supply was unusually inelastic compared to prior booms. We find that operational and labor market issues (e.g., disruptions to loan officer licensing) made it more difficult for lenders to expand their workforces and led to longer processing times and closing delays, exacerbating "usual" capacity constraints documented in Fuster et al. (2024). Further, we present novel evidence that these capacity constraints were national in scope because the mortgage market is geographically integrated. Finally, we study whether digital and online lending has ameliorated capacity constraints—here, 2020-21 is a key litmus test since it was the first refinancing boom since the widespread adoption of these technologies.[13] We in fact find little evidence that technology-based lenders expanded lending more elastically than other nonbanks; this and the low overall elasticity in 2020-21 suggest that technology has not yet "solved" the problem of capacity constraints.

IV.A Was 2020-21 Consistent With Historical Patterns?

We first study whether the historical relationship between intermediation markups and capacity utilization can account for the high markups in 2020-21. Figure 4 plots mortgage demand against the two measures of markups we have used already: the primary-secondary spread and the gain-on-sale.[14] Our preferred proxy for demand is the dif-

up over 900% from 2019. More broadly, if we multiply net production income per dollar of originations by average origination volume per firm in the MBA data, the resulting total net production income skyrocketed from below \$5mn in 2020:Q1 to an average of \$21.4mn over Q2-Q4, with a peak of over \$27mn in Q3.

[13] Online lending was rare up to the mid-2010s (Buchak et al., 2018; Fuster et al., 2019), but by 2020, 91% of lenders offered digital applications through an online portal (ICE Mortgage Technology, 2021).

[14] Note that for scatter plots and regressions, we adjust the Freddie Mac PMMS rate so that it reflects the rate for a loan with zero points. To do this, we take the mortgage rate and add the average points reported

ference between the weighted average coupon (WAC) on the stock of mortgages and the 10-year Treasury yield. This measure is highly correlated with applications for (refinance) loans and is arguably exogenous to mortgage supply shocks—or more precisely, the supply of intermediation in the mortgage market—because it does not rely on current mortgage rates.[15] We alternatively use the MBA mortgage applications index as a direct measure of demand. (These two series typically co-move closely; see Panel C of Figure 1.)

Figure 4 shows that markups during the pandemic significantly exceed what would be predicted simply from the level of demand. Red squares in the figure are from 2020 and green diamonds from 2021, with the number indicating the month. Blue circles are from 2012-19. There is a clear positive historical relationship between markups and mortgage demand. But from about April 2020 onward, markups are well above the line of best fit, before declining later in 2021, regardless of which demand or markup measure is used.

Table 1 quantifies the "excess" markup by regressing the primary-secondary spread or gain-on-sale on either demand proxy as well as time dummies corresponding to different phases of the pandemic. In all cases, the pandemic dummies indicate large, statistically significant excess markups from March 2020 through the first half of 2021. The historical relation between markups and demand can account for only about 20-45% of the rise in intermediation markups, depending on the specification.[16,17]

by Freddie Mac multiplied by a weekly point-rate trade-off. We estimate this point-rate trade-off using Optimal Blue Insight data, where we observe the offered interest rates for loans with different numbers of net points (+2, +1, 0, –1, and –2). For years prior to 2017 when Optimal Blue data are not available, we estimate this point-rate trade-off by using MBS prices at different coupons (which gives similar results).

[15] In contrast, using the spread between WAC and the current *mortgage* rate may produce bias in the estimated markup relationship, because mortgage rates reflect the intersection of demand and supply. Note that we study the equilibrium price in the primary market for mortgage *intermediation*; thus the requirement for our demand proxy is that it does not affect the supply of intermediation services, which appears reasonable for the WAC−10-year Treasury spread. See Fuster et al. (2024) for more detailed discussion.

[16] On the high end of this range, the coefficient in column 4 would project a maximum increase in gain-on-sale of 123bp, given that the MBA applications index increased from an average of 533 in January 2020 to a maximum of 1,204. This compares with an actual increase in gain-on-sale of 273bp.

[17] The pandemic dummies from March through September are comparatively smaller for gain-on-sale than for the primary-secondary spread, taking into account that the latter is a flow measure while the former measures the total gain earned by intermediaries. This reflects (i) a flattening of the relationship between gain-on-sale and the primary-secondary spread during the pandemic, and (ii) the fact that gain-on-sale is below the line of best fit at the start of 2020, while the primary-secondary spread is close to its fitted value.

Specifically, column 1 shows that the primary-secondary spread is 73bp higher than expected in March and April 2020, and 81bp higher than expected in May through September. For comparison, the one-standard-deviation (std) residual from this regression excluding 2020-21 is only 8.9bp (last row of table). Thus, one could consider the COVID-19 period roughly a "9 sigma" event for over six months before its effects slowly subside through to late 2021. Results are similar in column 2. The excess markup is also highly significant when we use gain-on-sale as the dependent variable (columns 3 and 4). Gain-on-sale is \$0.91 to \$1.13 higher than expected in March-April 2020, rising to \$1.21 to \$1.59 in May-September 2020, and remains highly elevated until the second half of 2021.

IV.B Operational Constraints in Expanding Capacity

Next, we present evidence that operational and labor market issues related to the pandemic made it more difficult than usual for lenders to expand capacity and can account for the low elasticity of mortgage credit supply in 2020-21.

Much of our evidence focuses on labor market frictions in hiring employees to cope with the surge in demand. Our analysis is motivated by anecdotal reports from mortgage industry participants that the abrupt, unexpected shift to a remote-work environment created significant challenges in hiring and training loan officers, processors, and other workers.[18] Labor supply was further held back by pandemic-related disruptions to the licensing of mortgage loan officers through the NMLS, a process involving background checks, fingerprinting, an exam, and ongoing education.[19] Early in the pandemic, half of fingerprinting locations were shuttered, with 10% still closed in December 2020. Testing

[18] E.g., one practitioner told us it was difficult to remotely train and monitor new employees; as a result lenders prioritized hiring experienced, trusted professionals (generally from competitors) requiring less training and oversight. Similarly, an executive at nonbank Mr. Cooper explained their limited growth as follows: *"It reflects the fact that we add capacity at a deliberate pace with an eye on the long term. And additionally, when the crisis hit and we shifted to work-from-home status, that slowed our hiring and our onboarding"* (Ivey, 2020).

[19] A new license is required for de novo loan officers as well as officers shifting from banks to nonbanks or moving across states. In these latter cases, the officer may temporarily operate for 120 days before obtaining a new license (Mortgage Bankers Association, 2019). We were told, however, that in some cases licensing delays exceeded this 120-day grace period.

sites also closed initially, although remote testing became available in September.[20] The pandemic also created operational challenges in closing loans—e.g., office closures made it difficult to document borrower employment and income, high layoffs often required checking employment multiple times (Berry and Kline, 2020), and county recorder offices were closed or on limited schedules (Hughes, 2020).

We now present evidence on the effects of these operational and labor market frictions on the quantity and cost of labor, loan officer licensing, and delays in loan closings.

IV.B.1 The Quantity and Cost of Labor

One test of whether lenders had difficulty in expanding employment is whether there was an unusual increase in the capacity utilization of the existing labor force. Evidence on this point is presented in Panel A of Figure 5, which plots the number of loans originated per sales employee (i.e., loan officer), using MBA data. Monthly originations per employee jumped from 5.3 in 2020:Q1 to 7.5 in Q2, and then exceeded 8 until 2021:Q2.[21] Labor utilization usually rises in periods of high demand, but as the figure shows, this does not account for the levels reached in 2020-21, which also far exceed any point over the previous decade including the 2012 refinance boom.[22]

MBA data also show that the price of labor was unusually high (Panel B of Figure 5). Labor costs per dollar of lending typically fall significantly during booms due to scale economies. But during the pandemic, sales employee costs scaled by loan volume were 20-25bp higher than expected based on historical patterns, equivalent to more than 10% of average total personnel costs measured over the previous five years.[23]

[20]One practitioner told us by email that: *"Testing centers closed at times and have had limited availability. This has prevented new LOs [loan officers] from joining the industry right away. We have seen delays of anywhere from a few weeks to a few months depending on the restrictions in the area."*

[21]Originations in the first quarter of 2020 were still relatively low because they mostly reflect applications from the last quarter of 2019, before the surge in refinancing activity.

[22]Appendix Figure A.7 plots the time series of originations per sales employee and per employee overall. Although labor utilization for non-sales employees also increased in 2020, this uptick aligned with patterns observed in earlier periods of high demand (e.g., 2012), suggesting that the labor shortage in 2020-21 was most acute for loan officers and other sales personnel.

[23]Notably, personnel costs stayed high in 2021 even as capacity constraints started to ease, likely because loan officers were able to lock in attractive compensation packages at the peak. We show in Appendix Figure A.7

One possibility is that lenders did not want to hire more in 2020 because they thought the boom would be short-lived. This is not consistent, however, with Panel C of Figure 5, based on Burning Glass data, which shows a dramatic increase in new job postings for loan officer positions early in the pandemic. Monthly postings peaked in August 2020; overall, in 2020:Q3, the volume of job postings was more than 2.5 times its level one year earlier. The overall level of postings in 2020-21 far exceeded any other period since 2010.

IV.B.2 Loan Officer Licensing

Next, we test whether loan officer licensing volume was unusually low by comparing realized outcomes to a counterfactual computed as the out-of-sample prediction from a time-series regression of $\log(licenses)$ on four lags of $\log(mortgage\ applications)$ and a December seasonal dummy. We construct licensing volume by aggregating NMLS micro-data. The model is estimated using pre-pandemic data from February 2015 to February 2020.[24]

Results reported in Panel D of Figure 5 indicate a significant licensing deficit. The model predicts a rise in licensing in 2020-21 reflecting the growth in applications. But instead, license issuance dropped by about half in spring 2020 and even the flow rate did not recover to its pre-pandemic level until late 2020. Integrating the difference between "actual" and "counterfactual" licensing implies a cumulative deficit in licenses issued of 11,200 by October 2020.[25]

IV.B.3 Processing Times and Delays in Loan Closing

Finally, we study the effects of labor shortages and other operational bottlenecks on mortgage processing. We first focus on processing times as measured in the confidential-use

that compensation costs for non-sales employees were also unusually elevated, although to a lesser degree in line with the evidence on quantities discussed above.

[24] See Table A.1 for the regression coefficients. The counterfactual series plotted in Figure 5 is based on our preferred specification, column 1. Licenses typically track loan applications with a two-month lag. We include only a dummy for December, not the other calendar months, because of the clear year-end drop in licensing evident in Panel D of Figure 5.

[25] Over the previous five years, the average number of new licenses over the March-October period was 46,700, meaning the deficit amounts to about one-quarter of that number.

HMDA data, defined as the gap between application and origination dates (following, e.g., Fuster et al., 2019, 2024). We regress processing time in days (winsorized at the 1st and 99th percentile) on borrower and loan characteristics (including loan purpose), county dummies, and dummies for loan application month. Panel A of Figure 6 traces out the coefficients on these month dummies, with February 2020 as the base category. The figure shows that processing times were substantially higher from March 2020 onward, initially by about 6 days, rising to 11-13 days at the peak from July to September 2020. This is a large increase relative to the pre-pandemic average processing time of about 48 days. (Figure A.8 plots the evolution of median processing time over 2012-2021 and shows that it moves closely with application volume, especially for refinances.)

Second, we use NSMO data to directly study closing delays. This survey asks borrowers four yes/no questions related to delays in the mortgage closing process. We construct a dummy equal to 1 if a respondent answered yes to any question.[26] Similar to the processing time analysis, we regress this dummy on origination month dummies and loan controls (e.g., credit score, loan size bins, income, components of wealth, risk aversion, race, ethnicity). Panel B of Figure 6 traces out the monthly coefficients, showing a significant increase in the propensity to experience a delay in loan closing from August 2020 onward.[27] The magnitude of the effect is quite large—the estimated incidence of any delay is 30-50% higher in the second half of 2020 than in the pre-pandemic period.

IV.C Are Capacity Constraints Local or National?

While we have so far focused on mortgage rates at the national level, it is quite striking that rates evolved very similarly across the country, as illustrated in Figure 7. Panel A shows (based on Optimal Blue Insight data) that although mortgage rates do vary across

[26]Borrowers are asked whether: (i) they had to redo/refile paperwork because of loan processing delays; (ii) they had to delay or postpone their closing date; (iii) loan documents were not ready at closing; (iv) the closing did not occur as scheduled. The pattern of our results is very similar if we use a composite indicator summing across the four questions (with values ranging from 0 to 4) instead of a dummy.

[27]This timing broadly lines up with Panel A, since in Panel B time is indexed by origination month, which is typically about two months after the application month but likely longer for loans experiencing delays.

metro areas, the differences were consistently small over 2020-21. Panel B, looking in the cross-section, shows that mortgage rates fell by similar amounts across metros during the pandemic (comparing March-December 2020 to October 2019-February 2020), generally within a few basis points, as seen by the proximity of most metros to the 45 degree line.

What explains this uniformity, and how can it be reconciled with a capacity constraints interpretation of the evidence, given that there was local variation in mortgage demand, economic conditions and the spread of the virus? We argue there are two main parts to the story. First, as in prior refinancing booms, the surge in mortgage demand was in fact quite aggregate in nature (Panel C of Figure 7). While there is of course some cross-market variation, the figure shows that demand increased strongly everywhere as rates fell; e.g., year-over-year application growth averaging over 2020 was 42% at the 25th percentile of the distribution compared to 58% at the 75th percentile.

Second, the US mortgage market is, to an underappreciated degree, highly integrated geographically, with human resources and capital able to shift quite freely across locations in response to local shocks.[28] Specifically, we find novel evidence that lenders, and even individual loan officers, were geographically diversified even prior to COVID, and further that this geographic diversification *increased* as demand surged in 2020, despite pandemic-era frictions which conceivably could have constrained resource flows.

Evidence on these points is presented in Panel D of Figure 7, which constructs measures of the geographic dispersion of lending using HMDA data. For each application we compute the number of distinct core-based statistical areas (CBSAs, effectively a metro area) where the lender, and also the loan officer of record, was active in the same month, where "active" means they received at least one application. We then take the mean and

[28] As concrete examples, the two largest lenders in our sample period, Rocket Companies and United Wholesale Mortgage (UWM), operate in all 50 states without any significant local labor market presence at all. Instead, the workforces of both these firms are centered in their head offices in Michigan, to be shifted across markets or products as needed. (E.g., the 2022 10-K for UWM states: *"As of December 31, 2022, we had approximately 6,000 team members, substantially all of whom are based in our corporate campus in Pontiac, Michigan."*). As further illustration of geographic integration, it is standard for lenders to centralize mortgage underwriting and processing through regional or national hubs. E.g., for Wells Fargo, many back-office activities are centralized in Des Moines, Iowa, and a second mortgage hub near Minneapolis (Weil, 2019).

median of these "active CBSAs" variables across all HMDA applications in the month.

We find that pre-COVID, the originator of a typical loan was active in 250-350 CBSAs in the same month, indicating a high degree of geographic dispersion.[29] While there is a long tail of small lenders, most loans are made by intermediaries active in many markets able to shift financial capital and organizational resources across regions depending on demand. Moreover, lenders expanded to new markets in 2020-21 to become progressively *more* geographically diversified, aside from a temporary blip in March 2020.

Even if lenders are national, local capacity constraints might still bind if individual mortgage professionals are closely tied to individual markets. Panel D of Figure 7 also finds, however, that in 2019 the loan officer for a typical mortgage operated in a mean of 9 different CBSAs in the same month, and a median of 3 CBSAs. Furthermore, as demand spiked in 2020, loan officers significantly expanded the number of markets in which they operated—-the average increased from about 9 to 12, while the median rose from 3 to 5.

To confirm that these facts are not due to compositional shifts, Table 2 estimates linear models at the lender or loan officer by month level tracing out how "active CBSAs" (measured in logs) changes over time conditional on lender or loan officer fixed effects. Columns 1 and 4 show that geographic dispersion of lending activity is strongly positively related to the volume of applications received. Columns 2 and 5 show that dispersion increased after March 2020 (relative to the prior six months), by up to 30% at the loan-officer level and 20% at the lender level. For lenders, the rise in the number of active CBSAs is explained by the high rate of application growth; for loan officers, geographic dispersion rose even more than application growth would predict (columns 3 and 6).

The ability of lenders and loan officers to shift across locations and enter new markets as needed implies that the key constraint on credit supply is *aggregate* industry resources rather than local capacity tied to the specific market. As a further test of this hypothesis, we examine directly whether capacity constraints (measured by processing time or

[29]For reference, there are 849 CBSAs in the data, of which only 353 have a population of 100,000 or more.

mortgage rates) in 2020 were more binding in locations experiencing faster application growth. Evidence is reported in the form of binned scatter plots in Figure A.9. Panels A and B of the figure show that the large increase in processing time we documented earlier is remarkably insensitive to local year-over-year application growth, while Panel C finds the same thing for mortgage interest rates.

In short, while we have seen earlier that mortgage demand correlates strongly with intermediation markups and processing times in the time series (see also Fuster et al., 2024), there is little or no relation in the cross-section, reflecting that industry resources are sufficiently mobile to offset local demand shocks.

IV.D Did Technology Help?

The low mortgage supply elasticity in 2020-21 is particularly striking in light of the recent wave of technological innovation to digitize lending and put the application process online (Buchak et al., 2018; Fuster et al., 2019). While such technology has significant promise to mitigate capacity constraints through automation, the fact that credit supply was *less* elastic in 2020-21 than prior booms suggests, prima facie, that recent technological change has not significantly relaxed industry capacity constraints.

That said, it is possible that new technology did help, but its benefits were overwhelmed by the operational and labor market frictions discussed earlier. Therefore, as a more direct test, we study the performance of technology-based, or "fintech," lenders, specifically whether such lenders were able to increase lending more rapidly or process loan applications faster than other originators during the 2020-21 boom.

We use a classification of fintech lenders from Jagtiani et al. (2021), which itself builds on Buchak et al. (2018) and Fuster et al. (2019).[30] These classifications are based on whether lenders offered online applications as of 2016, but we posit that it may still be reasonable to rely on them in 2020-21 if these "early adopters" (e.g., Rocket Mortgage) re-

[30] The lenders classified as fintechs are: AmeriSave, Better Mortgage, CashCall, Homeward, Everett Financial (Supreme), Guaranteed Rate, LoanDepot, Movement Mortgage, SoFi, and Quicken (Rocket Mortgage).

main near the technological frontier. Supporting this assumption, Figure A.10 shows using HMDA data that fintechs were indeed still able to process observably similar loans 6-7 days faster than other nonbanks in late 2019 and early 2020, just before the pandemic.[31] (Interestingly though, we find the "fintech advantage" in processing speed has diminished over time as online lending has become widespread, by about half a day per year.)

We then estimate linear models using loan-level HMDA data in which we regress a dummy for whether the lender for a given loan is a fintech on a pandemic dummy and loan characteristics, thereby measuring the (conditional) change in the fintech market share. We restrict the sample to conventional conforming originations with an application date between July 2019 and December 2020; that is, we focus on the first 9 months of the boom when markups were particularly high and a "pre" period of similar length.[32]

Results are presented in Table 3. In column 1, which includes banks and nonbanks and has no controls, we find a significant 2.6 percentage point (pp) increase in the fintech market share during the pandemic, compared to a sample average of 16%. However, the rise in the fintech share is significantly smaller when we restrict the sample to nonbanks (column 2), a more comparable sample because all fintechs are nonbanks and the nonbank share of lending rose in 2020-21 (see Section V). And after also controlling for loan characteristics (column 3), the change in the fintech share is essentially zero—the confidence interval rules out an increase larger than 0.5pp.[33] Column 4 of Table 3 does however find

[31] Results are based on a loan-level linear model of processing time estimated month-by-month from January 2012 to December 2021, conditioning on the controls from Table 3 of Fuster et al. (2019). We estimate results separately for purchase loans and refinances, restricting to conventional conforming first-lien mortgages.

[32] We use HMDA data through 2021 and consider all loans with an application date within our sample window even if the loan did not close until 2021. This is important to avoid selectively excluding some loans that were slow to close. Table 3 includes both purchase mortgages and refinances, although we estimate results separately by loan purpose in Appendix Table A.2; results are generally similar for the two types.

[33] While we include a rich set of controls (see notes to Table 3 for the full list), the change in the coefficient from columns 2 to 3 is similar if we control only for a refinancing dummy. This reflects the fact that fintechs specialize in refinances, which became a larger overall share of lending during the pandemic. Looking beyond average effects, Figure A.11 plots the dynamics of the fintech share of nonbank conforming lending separately for purchase mortgages and refinances, based on the regression model from column 3 of Table 3 but replacing the pandemic dummy with month dummies. For purchase loans, the fintech share rises at the onset of the pandemic, by up to 2pp, but the effect dissipates by June. For refinances, the fintech share is quite volatile from month to month, meaning that estimates of how the fintech market share changed during the pandemic depend on the length of the pre- and post-period chosen. Finally, we note that in fact

that fintechs pivoted towards low-credit-score loans, which Sharpe and Sherlund (2016) argue are rationed during booms because they are more labor-intensive to underwrite, suggesting technology may have promoted the flow of credit in that segment.[34]

Columns 5-7 instead study processing time in days. The negative coefficient on "fintech" confirms that fintechs were able to process mortgages faster than other lenders prior to the boom. While fintechs were also faster during the pandemic itself, the small positive interaction term shows that the "fintech advantage" over other nonbanks if anything *declined* slightly during the boom, by up to 2 days.[35] This again suggests that capacity constraints during the pandemic were at least as binding for fintechs.

In short, while revealed preference shows consumers value the speed and convenience of online lending, evidence from the pandemic suggests that technology has not yet "solved" the problem of capacity constraints during periods of peak demand, perhaps due to bottlenecks in the origination process that are hard to remove by technology alone.

V Alternative Mechanisms

We now consider several other plausible drivers of high markups in 2020-21. First, we study the role of financial constraints faced by nonbank lenders as a potential brake on credit supply. We find that the nonbank share of lending indeed fell temporarily early in the pandemic, although this seems related to nonbanks' greater reliance on third-party brokers rather than capital or liquidity constraints—further, after this initial dip, nonbanks expanded lending *more* than banks. We then turn to explanations related to default

this evidence is quite consistent with what Fuster et al. (2019) find for an earlier sample period: while fintech lenders were able to process loans faster when application volumes rose, they did not expand market share.

[34] Consistent with Sharpe and Sherlund (2016) and Frazier and Goodstein (2023), Appendix G.2.3 shows that processing times on low-FICO mortgages are indeed higher in the conventional conforming market.

[35] In contrast, Fuster et al. (2019) find during an earlier period that processing speed is less sensitive to credit demand shocks for fintechs than other lenders. The difference between our findings and these earlier results may reflect the widespread diffusion of online lending over the intervening period. Note also that the monthly coefficients shown in Appendix Figure A.10 indicate that for refinances, fintech lenders' processing speed advantage over other lenders fell sharply over the first four months of the pandemic, but then increased again and was significant during the remainder of 2020-21. For purchase loans, initial relative changes were small but then fintech lenders became faster in the second half of 2020, especially Q4.

and forbearance risk, direct health and economic effects of the virus, and lender market power, finding that none of these factors played an important role.

V.A Nonbank Financial Frictions

Our analysis of lender financial constraints focuses on nonbank mortgage companies, which faced significant liquidity strains early in the pandemic, including margin calls on hedges, liquidity outflows due to mortgage forbearance, and concerns about the continued availability of warehouse funding (Loewenstein, 2021; Pence, 2022). These stresses are important because nonbanks are now central to the US mortgage market, having originated the majority of loans in recent years (Buchak et al., 2018; Kim et al., 2022). Nonbanks are fragile because they are financed by short-term wholesale debt and lack access to liquidity backstops available to banks such as the discount window and Federal Home Loan Bank advances (Kim et al., 2018; Jiang et al., 2020). Banks also experienced large deposit inflows in 2020, and Li et al. (2020) find they were not liquidity constrained as a result.

We test whether financial frictions constrained nonbank lending in two ways. First, we examine whether, in aggregate, the nonbank share of lending fell as the pandemic took hold. Second, we study the cross-section of nonbanks to see whether mortgage companies with low liquidity or capital ratios lost market share to rivals with stronger balance sheets. Our analysis is based on HMDA data merged with nonbank characteristics from the Mortgage Call Reports, as described in Section II.

V.A.1 Time-series Shifts in the Nonbank Share

Figure 8 plots the evolution of the nonbank share of conforming mortgage lending, as well as the conditional share controlling for county fixed effects and/or loan characteristics. Time is indexed by application date, the more relevant date for loan pricing and credit availability. The nonbank share initially increased in February and early March 2020 as mortgage applications spiked, but then fell sharply starting in mid-March—the unconditional nonbank share dropped by about 5pp while the conditional share fell by about 3pp. This decline was short-lived, however. The nonbank share surpassed its pre-pandemic level by late April, then rose further, reaching 64% by December 2020, a full 9pp *higher* than a year earlier. These patterns are robust to the controls used.

This suggests financial frictions may have constrained nonbank lending, but if so, the effect lasted only a month or two. This seems consistent with the chronology detailed in Loewenstein (2021) and Pence (2022). Nonbanks faced significant financial pressure in March and April, sparking calls for an industry bailout; but by May, nonbank liquidity began to benefit from the prepayment "float" generated by the refinancing wave.[36] Government actions also stabilized the industry: e.g., Ginnie Mae announced a temporary backstop facility for nonbanks on April 10 (Ginnie Mae, 2020), and on April 21, the FHFA set a four-month cap on servicing advances for loans in forbearance (FHFA, 2020).

Extending this graphical evidence, Table 4 reports estimates from linear models in which we regress a dummy for whether the lender is a nonbank on time dummies and various controls.[37] Column 1 traces out the raw nonbank share of conforming lending, which rises by 0.8pp early in the pandemic, drops to 1.3pp *below* pre-pandemic levels during the peak stress period (March 13-April 30), then rises to 6.8pp above pre-pandemic levels on average in May-December. Results with controls are similar (columns 2 and 3).

Columns 4 and 5 focus on low-credit-quality loans that may have more funding risk (e.g., because of a higher risk of defects that disqualify loans from being securitized). The nonbank share does indeed rise by less for loans with low credit scores and high LTVs, but nonbanks still gain significant market share for such loans. Finally, column 6 drops fintechs from the sample to check whether the rise in the nonbank share simply reflects a shift to online lending; results show that this is not the case, consistent with Section IV.D.

[36]Cash inflows from prepayments are retained by the servicer temporarily before the funds are forwarded to investors (see Pence 2022 for details). Although mortgage application volume started rising sharply in late February, it took a couple of months before this translated into a rising "float" for servicers, because during this period it took about 60 days on average for a typical loan to be closed and funded.

[37]The "base" pre-period is December 2019 to mid-February 2020; we use a short pre-period because of the upward drift in the nonbank share earlier in 2019 evident in Figure 8.

V.A.2 Cross-sectional Evidence

We turn to cross-sectional analysis to shed light on the mechanisms underlying these shifts. Financial constraints are a natural explanation for the temporary dip in the nonbank share in March-April 2020, but other stories are also plausible. For example, nonbanks rely more heavily on brokers and correspondent lending—so-called "third-party originations" (TPOs)—and the third-party channel declined sharply at the start of the pandemic, likely because economic uncertainty led lenders and investors to want tighter control and oversight over the origination process (Recursion Inc. 2022; Figure A.12).

To proceed, we collapse the HMDA-MCR data by lender and week, and estimate a Poisson model of conforming lending as a function of nonbank characteristics (measured as of 2019:Q4) during different phases of 2020. Results are reported in Table 5.[38] We standardize each characteristic so that coefficients measure the percentage change in lending for a one-standard-deviation change in the characteristic. Specifications include lender and week fixed effects, and standard errors are clustered by lender.

We consider two measures of financial condition: liquidity as measured by the ratio of cash to total assets, and the equity capital ratio. In both cases, we find little indication that nonbanks with stronger balance sheets expanded lending faster, either in the univariate specifications in columns 1-5 or the multivariate regressions in columns 6-7. This is true even during the "peak stress" period (mid-March to April 2020), where the point estimates on capital and liquidity are indeed positive, but not significant.

We do however find evidence that mortgage companies reliant on a TPO business model experienced lower lending growth, at least initially.[39] In column 6, a one-standard-deviation increase in the ex-ante TPO share is associated with 8% lower lending in the

[38]We study the full cross-section of nonbanks, but since nonbank lending is quite concentrated, column 7 of Table 5 re-estimates the multivariate model from column 6 restricting the sample to nonbanks with at least $1bn in assets as of 2019:Q4. The resulting point estimates are quite similar to column 6, although the estimates are less precise due to the much smaller sample (this screen reduces the sample size by 92%).

[39]We measure reliance on third-party originations using a HMDA variable for whether the borrower applied for their loan through a third party rather than directly to the lender. We define "TPO share" as the mean of this variable at the lender level, measured over the five months prior to our regression sample period.

"early pandemic" period and 18% lower lending in the "peak stress" period, significant at the 1% and 10% levels, respectively. The effect dissipates over the remainder of 2020, although the point estimate remains negative.[40]

Interestingly, we also find that smaller nonbanks expanded lending faster in 2020 (statistically significant except for the "peak stress" period), perhaps because small organizations were more nimble in a rapidly changing environment. This result is further evidence that financial constraints were not a major drag on lending, since such constraints would likely be amplified for small nonbanks. Finally, the model includes a fintech dummy; consistent with Section IV.D, we find little evidence of a significant shift in the fintech share of nonbank lending over 2020, with or without other lender controls.

Looking outside the conforming market, Figure A.13 finds a larger and more persistent decline in the nonbank share of lending in the jumbo market. Why? Nonbank jumbos are typically sold to banks, who likely sought more control over underwriting given that jumbos are not guaranteed;[41] the pandemic also saw a drop in jumbo securitization, the other main funding option for nonbanks (Federal Reserve Board, 2021). In contrast, the nonbank share of FHA/VA lending rose in 2020-21 similarly to the conforming market (Figure A.14), reflecting continued funding through the government-backed agency MBS market. These results highlight the dependence of nonbank mortgage lending on the availability of liquid secondary markets (as also studied in Buchak et al., 2024).

V.B Forbearance and Default Risk

The pandemic led to a surge in mortgage forbearance and non-payment, reflecting high unemployment and a CARES Act provision requiring servicers to provide up to a year

[40] We also re-estimated our loan-level model including the TPO dummy as an additional control as a different way to evaluate this channel. Results shown in Table A.3 are consistent with Table 5: controlling for loan channel increases the coefficient on the nonbank dummy in the first two pandemic stages and somewhat reduces the drop in the nonbank share between the "early pandemic" and "nonbank stress" periods.

[41] E.g., Wells Fargo entirely stopped purchasing jumbo mortgages from third parties early in the pandemic, even though it continued to originate some jumbos through its own retail channel (Eisen, 2020).

of forbearance on federally backed mortgages.[42] Non-payment is costly for mortgage intermediaries, even in the conforming market where loans are securitized and carry a credit guarantee. First, there is liquidity risk because the servicer must advance mortgage payments, taxes, and insurance even if the borrower stops paying. These advances will eventually be reimbursed, but funding them in the interim may be expensive or infeasible.[43] Second, there is "pipeline" risk that the loan becomes delinquent before it can be sold.[44] Third, servicing a delinquent loan is much more labor intensive and costly.

We use cross-sectional variation to study whether this heightened default risk led to a risk premium that increased mortgage rates for conforming borrowers. Our approach uses the fact that the increase in the non-payment rate was up to an order of magnitude higher for low-credit-score borrowers (see Appendix F.1). If rising default risk is priced into mortgage rates, we should therefore see an increase in the interest rate *spread* between low-score and high-score conforming loans.

We first estimate this default risk premium using Optimal Blue Insight data, which include offer rates for otherwise identical mortgages with a FICO score of 680 and 750. We measure the rate premium for the FICO 680 loan by estimating the regression:

$$\text{rate}_{imt} = \alpha_{mt} + \beta_t \times (\text{FICO}_i = 680) + \varepsilon_{imt}, \tag{4}$$

where rate_{imt} is the interest rate on an offer i in CBSA m during week t, $FICO_i = 680$ is a dummy for a FICO score of 680 rather than 750, and α_{mt} is a set of CBSA$\times$week fixed effects. Other loan characteristics are held fixed (e.g., DTI=36, LTV=80 and balance of \$300K). β_t then traces out the evolution of the FICO 680-750 interest rate spread.

[42] At the peak in June 2020, 8.6% of mortgages were in forbearance (source: MBA). The total mortgage non-payment rate more than doubled from 3.2% in January 2020 to 7.8% by May (Black Knight, 2020).

[43] This was a cause of great concern in the industry early in the pandemic. On April 21, 2020, it was announced that servicing advances for conforming mortgages securitized by Fannie Mae and Freddie Mac would be capped at four months of principal and interest (FHFA, 2020). This cap did not apply to taxes, insurance, and other payments, however.

[44] Such loans typically would be sold privately at a significant discount. The GSEs and FHA took some steps to limit pipeline risk during the pandemic, but these steps only partially protected lenders (e.g., the GSEs agreed in April 2020 to purchase loans in forbearance, but only at a 500–700bp discount (ABA, 2020)).

We also compute an analogous spread using Optimal Blue rate locks data, estimating:

$$\text{rate}_{ilmt} = \alpha_{mt} + \delta_{lt} + \beta_t \times \text{FICO bin}_i + \Gamma X_{ilmt} + \varepsilon_{ilmt}, \tag{5}$$

where rate_{ilmt} is the interest rate on lock i issued by lender l in CBSA m during week t; FICO bin_i includes five FICO bin dummies; α_{mt} and δ_{lt} are CBSA$\times$week and lender$\times$month fixed effects; and X_{ilmt} is a set of controls including log loan amount, DTI, DTI^2, and dummies for lock period and property type. For loans with discount points or credits, we convert the lock rate to a zero-points equivalent interest rate using the market rate-point trade-off measured each week in Optimal Blue Insight.[45]

Estimates of β_t from these two models are reported in panels A and B of Figure 9. We find no evidence of a persistent increase in the rate spread on low-FICO loans for either offers or rate locks. The spread did spike temporarily in March 2020, but by April it returned to a narrow band around 40bp, at or even slightly below pre-pandemic levels.

Data on quantities paint a similar picture. Panel C of Figure 9 plots the number of conforming lenders that offered mortgages to borrowers with different FICO scores, calculated by averaging the number of rate offers in the Optimal Blue Insight data across the 20 Case-Shiller metropolitan statistical areas. The number of lenders drops temporarily in March, and more so for lower FICO loans, but it is subsequently quite stable, with little evidence of rationing to riskier borrowers. Panel D plots the percentage of conforming rate locks below two FICO thresholds (680 and 640). For purchase loans (the two solid lines), there is no evidence of a drop in the fraction of low-FICO rate locks. There is a drop for refinances, but this is typical during a refinancing boom because high-FICO borrowers refinance more quickly when rates fall (Keys et al., 2016).

To sum up, we find heightened default risk was not an important driver of high markups on conventional conforming loans during the pandemic. Default risk was however more significant for rates in the high-risk FHA market, as we discuss in Section VI.

[45] The procedure is detailed in footnote 14. An alternative approach is to directly control for points and credits interacted with time dummies in equation 5; this generates similar results.

V.C Macroeconomic and Health Shocks

Although we find little role for individual default risk, perhaps mortgage rates incorporated a more general risk premium due to the direct macroeconomic and public health effects of the virus. In this case, we may expect to see heterogeneity in rates by *location*, depending on the severity of the pandemic and the drop in economic activity. Recall from Figure 7 that while mortgage rates do vary across metro areas, the differences are typically small, and the change in interest rates after the pandemic began was very similar across metros. This suggests there is limited scope for local factors. Nevertheless, we now study whether the variation that does exist is linked to local macroeconomic and health shocks.

In Table 6, we examine variation in locked rates across the 100 most populous metro areas, focusing on the early stages of the pandemic when uncertainty and the economic effects of the virus were most acute. We regress interest rates (again, adjusted for points) from 1.1 million conventional conforming loans locked from November 2019 through August 2020 on CBSA fixed effects, loan characteristics interacted with week locked, and different proxies for how severely a metro area was affected by the health and economic effects of COVID-19.

The first variable we try is COVID-19 cases per thousand residents in the prior calendar month. In fact, a higher case rate is associated with slightly *lower* mortgage interest rates (column 1), although the effect is extremely small—a one-standard-deviation rise in the case rate is associated with only a 0.3bp drop in mortgage rates. Results are similar if we instead use a dummy for metros in the top quartile of cases per capita (column 2).

Next, we study the economic shock. Job losses, measured as the standardized year-over-year change in the local unemployment rate, are positively correlated with mortgage rates (column 3), but again the effect is not economically meaningful. A 1 std increase in unemployment is associated with a 1.1bp rise in mortgage rates. The national increase in unemployment (from 3.5% to a peak of 14.8%) corresponds to 2.7 standard deviations, or a rate impact of only 3bp. Alternatively, we use a measure of time spent at workplaces (from the Opportunity Insights Tracker, Chetty et al., 2023). One might expect that interest rates were higher in places where workplaces were shuttered, because of higher risk or difficulty in closing loans; directionally however we find the opposite, although the effect is again small, as seen in column 4. (Note: the sample size in this column is somewhat lower because "time-in-workplaces" is not available for all CBSAs in our sample.)

To summarize, we find no evidence that cross-metro variation in the spread of COVID and the economic effects of the virus was meaningfully priced into mortgage rates.

V.D Market Power and Shopping

Finally, we investigate whether lender market power can account for the rise in intermediation markups. Market power may arise through concentration; for example, Scharfstein and Sunderam (2016) find evidence of lower mortgage rate pass-through in concentrated mortgage markets. Alternatively, even if there are many lenders, each originator may enjoy market power if borrowers face switching costs or do not search extensively (Klemperer, 1987; Wolinsky, 1986). For example, it is possible that borrowers searched less actively once the boom began because they did not need to scour the marketplace to beat their current rate (see Bhutta et al., 2024 for related evidence).

We study the role of market power in several ways. First, following Scharfstein and Sunderam (2016), Table 6 tests whether mortgage rates fell by less in concentrated markets, using two ex-ante concentration measures derived from HMDA data interacted with a COVID-19 dummy (= 1 from March 14, 2020). In column 5, the concentration measure is the share of loans in 2019 originated by the metro area's top four lenders, while in column 6 it is the local Herfindahl-Hirschman Index (HHI). We find no evidence that concentration mattered for rate pass-through—neither interaction term is statistically significant, and the confidence bounds exclude an economically significant effect.

Second, we repeat this exercise using the market share of lenders that failed during the 2007-08 crisis, which Buchak and Jørring (2024) argue provides plausibly exogenous variation in post-crisis local mortgage market competition.[46] We find a correctly signed but economically minor effect (column 7 of Table 6); a 1 std increase in the failed lender share is associated with a 0.8bp larger fall in mortgage rates.

Third, we examine whether market concentration increased during the pandemic, measured by HHI or by the number of unique active lenders at the CBSA-by-month level (see Appendix E.1). By either metric, local markets in fact became *less* concentrated, consistent with our evidence from Section IV.C that lenders expanded to new markets as demand rose. In short, we find no evidence that the pandemic somehow limited the set of lenders that borrowers could access.

Fourth, we use NSMO data to study whether borrowers searched less actively or changed their shopping behavior during the pandemic, considering six outcomes such as whether the borrower seriously considered more than one lender or made use of many information sources when searching. Results are presented and discussed in Appendix E.2. To summarize, we find no evidence that borrowers searched less actively, although there is some evidence the pandemic led borrowers to put lower value on having a prior relationship with their lender, a shift which if anything would enhance competition.

Fifth, we use Google Trends data to study online mortgage search activity (Figure A.17). Mortgage search volume spiked to record levels in March 2020, and remained high through 2021. Further, the figure shows that search activity was unusually high relative to what would be predicted by the level of refinancing incentives.

In sum, we find no evidence that lender market power can explain the sharp increase in markups—borrowers were if anything searching unusually actively, local markets became less concentrated after the boom began, and interest rate pass-through was not closely connected to measures of local competition. Finally, Black Knight (2020) shows that servicer retention—the share of borrowers refinancing through their existing servicer—fell during the pandemic to only 18% by 2020:Q3, the lowest rate in at least 15 years.

[46] We thank Adam Jørring for providing us with a copy of this variable.

VI Credit Supply in Riskier Market Segments

Finally, we turn from conventional conforming mortgages to study credit supply in two other segments—the jumbo market and the FHA market. The jumbo market is a useful laboratory because it does not feature government guarantees and did not benefit directly from Fed QE. By comparing jumbo loans to conforming and "superconforming" loans, we estimate how government guarantees and QE separately played significant roles in supporting mortgage supply. That said, we also show that guarantees were not enough to fully stabilize lending in the FHA market, where credit availability also declined relative to the prime conforming market. Our key findings are summarized below. Full estimation results and further discussion are presented in Appendix G.

VI.A The Jumbo Market

Analyzing Optimal Blue data using the same methodology as in Section V.B, we find that the interest rate spread between prime jumbo loans and otherwise identical conforming loans increased sharply by 40-70bp at the start of the pandemic before gradually normalizing over the last few months of 2020 (see Appendix G.1). The number of lenders offering jumbo loans also dropped by more than half for prime borrowers, and fell to essentially zero for risky borrowers. The quantity of credit as measured by the share of jumbos in total lock volume also decreased. We confirm these patterns in HMDA data, finding that the share of jumbo originations declined by 30-50% during the pandemic (measured within a narrow 10% window on either side of the conforming loan limit).

This decline in credit availability in the jumbo market compared to the conforming market is consistent with an amplification of credit risk premia, given that jumbos do not carry government credit guarantees. But an additional factor is that conforming loans (but not jumbos) were purchased in large quantities by the Fed starting in March 2020 through its QE program.[47] To disentangle the effects of QE and government guarantees,

[47]The Fed purchased $580bn in agency MBS through the TBA market in March and April 2020 alone (Frame et al., 2021), and its agency MBS holdings increased rapidly from $1.37tr at the start of March 2020 to $1.90tr

we study the supply of *superconforming* mortgages. These are loans in high-cost areas with balances below the local conforming limit—making them therefore eligible for government guarantees—but above the national conforming limit, which for institutional reasons makes them much less likely to be purchased by the Fed.[48]

Appendix G.1 shows that the superconforming-conforming spread increased by about 25bp after Fed MBS purchases restarted in March, consistent with a QE channel. The effect dissipated by June, however. Studying quantities, we find that both QE and government guarantees seem to have promoted credit supply—lending dropped in relative terms just above *both* the national and local conforming limits during the pandemic (restricting our analysis to high-cost areas where the two limits are different). The estimates around the local limit are more persistent and larger relative to the sample mean, however, suggesting that credit guarantees had more significant effects. That said, our results provide new evidence that QE has "local" effects on lending—even within the conforming market, QE had larger supply effects for the specific mortgages likely to be purchased by the Fed.[49]

VI.B The FHA Market

While credit guarantees and QE were important, we find they were not enough to fully stabilize credit in the FHA market. Again using Optimal Blue data, Appendix G.2 finds a spike in the interest rate spread between higher-vs.-lower risk FHA loans starting in April 2020 and peaking in June, coincident with the post-CARES-Act surge in forbearance. The

by the end of June (source: Federal Reserve Bank of New York). The pace of purchases slowed after April 2020 but purchases continued until 2022. Importantly, Fed QE did not include purchases of nonagency MBS backed by jumbo loans. (To date, the Fed's long-term asset purchases have been restricted to credit-insensitive assets. The Fed did purchase corporate bonds in 2020, although this was done over a shorter period under the Fed's Section 13(3) emergency lending authority; see e.g., Gilchrist et al., 2024.)

[48] Specifically, the Fed buys agency MBS in the "to-be-announced" or TBA market, and pools comprising more than 10% of superconforming loans are not TBA eligible (Vickery and Wright, 2013; Huh and Kim, 2020). Matching data on the Fed portfolio holdings to eMBS loan-level data, we estimate in Appendix G.1 that superconforming loans are about 40% less likely to be purchased by the Fed.

[49] Here, we extend prior work which finds that QE boosts conforming mortgage lending relative to jumbo lending (e.g., Di Maggio et al., 2020). An advantage of our approach, which focuses on variation in QE within the conforming market, is that jumbo and conforming loans also differ in other ways (e.g., the former are not guaranteed, and have higher risk-weights for banks since they cannot be securitized into agency MBS).

number of lenders offering FHA loans also fell significantly in April, and the share of FHA purchase rate locks to low-FICO borrowers dropped by half. Intermediation markups also increased more rapidly in the FHA market. Appendix G.2 shows that the primary-secondary spread widened by 40-60bp more for FHA loans than conforming loans early in the pandemic; gain-on-sale also rose by more.

These results are consistent with an amplification of the risk premium for FHA lending which was then priced into mortgage rates. An alternative hypothesis, however, is that FHA lending was "crowded out" because capacity-constrained lenders wanted to focus on loans that were simpler to underwrite. While it is difficult to fully disentangle these two stories, we are able to shed some light by studying processing times for FHA loans and riskier conforming loans before and during the pandemic, as a proxy for processing complexity (see Appendix G.2.3). We show that FHA loans do take longer to originate, but that the same is true for low-FICO conforming loans, a segment where interest rate spreads did *not* widen relative to prime loans, as shown in Figure 9. This suggests that the increase in markups in the FHA market was not simply due to lenders adjusting their pricing to discourage applications from harder-to-process borrowers. Our results therefore provide some support for the view that policy interventions to limit the risks faced by FHA lenders (e.g., a Ginnie Mae liquidity facility as proposed by Kaul and Tozer, 2020) would help stabilize FHA lending during stress periods.

VII Conclusion

The 2020-21 pandemic period represents the most significant shock to US mortgage lending since the global financial crisis, and studying this episode yields new lessons about the functioning of this key market. While lending boomed, we find that an increase in intermediation markups limited the pass-through of low rates to households due to capacity constraints amplified by pandemic-related operational and labor market frictions. We find new evidence based on this period that capacity constraints are national in scope and have not yet been significantly mitigated by online and digital lending technologies. Nonbanks, which play an increasingly important role in the mortgage market, expanded lending more elastically than banks in 2020-21, but remain reliant on securitization. Studying the role of public policy, we find that government guarantees support the flow of credit to riskier borrowers but are not always sufficient. QE also supports mortgage supply and has local effects based on which conforming loans are purchased.

Stepping back, it is striking that in 2020, intermediaries collected as much as 5% of a mortgage's balance for the service of linking borrowers with savers. Moreover, most mortgages during this period were simple refinances; while careful underwriting of such loans is sensible from an individual lender's perspective, rate-and-term refinances lower systemic default risk even if *no* effort is spent in underwriting. Meticulously underwriting rate-and-term refinances in a period with binding capacity constraints not only raises costs, but may also crowd out harder-to-originate loans. Our findings, therefore, reinforce arguments for a larger role for streamlined refinances and adjustable-rate mortgages, or alternative mortgage designs that feature automatic adjustments during periods of stress (e.g., Eberly and Krishnamurthy, 2014; Guren et al., 2021; Campbell et al., 2021). As in the financial crisis, such contracts would have substantially strengthened the transmission of low interest rates during the pandemic.

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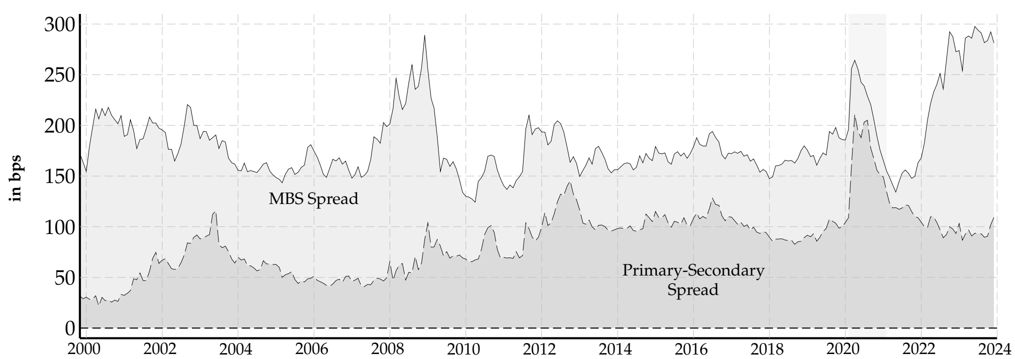
Figure 1: **Mortgage rates, Treasury and MBS yields, and mortgage demand.** Panel A displays time series of the 30-year fixed-rate mortgage (FRM) rate, the 10-year Treasury yield, and the MBS yield (based on interpolating between coupons, as explained in Section III.A.1). Panel B decomposes the spread between the 30-year FRM rate and the 10-year Treasury yield (shown by the solid line) into the MBS spread (= MBS yield minus 10-year Treasury yield) and the primary-secondary spread (= 30-year FRM rate minus MBS yield), as explained in Section III.A. Panel C shows market-wide mortgage application volume and the gap between the weighted average coupon (WAC) on outstanding mortgages and the 10-year Treasury yield (a proxy for refinancing demand). Data sources: Freddie Mac PMMS (30-year FRM Rate), J.P. Morgan Markets (MBS Yield, 10-year Treasury yield, WAC), Mortgage Bankers Association (MBA Application Index).

A. Rates & Yields

B. Components of the Mortgage-Treasury Spread



C. Application Volume & Proxy for Refinancing Demand

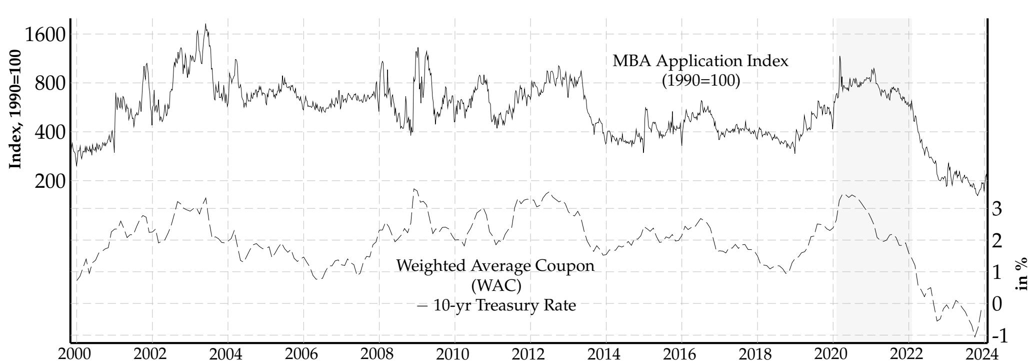


Figure 2: **Tracing the mortgage-Treasury spread over 2020–2021.** This figure decomposes the mortgage-Treasury spread into four components, based on the methodology described in Section III.A. The black dashed line shows the change in spread between the headline mortgage rate (from PMMS) and 10-year Treasury yields relative to the beginning of 2020, in basis points. Data sources: Freddie Mac PMMS, J.P. Morgan Markets.

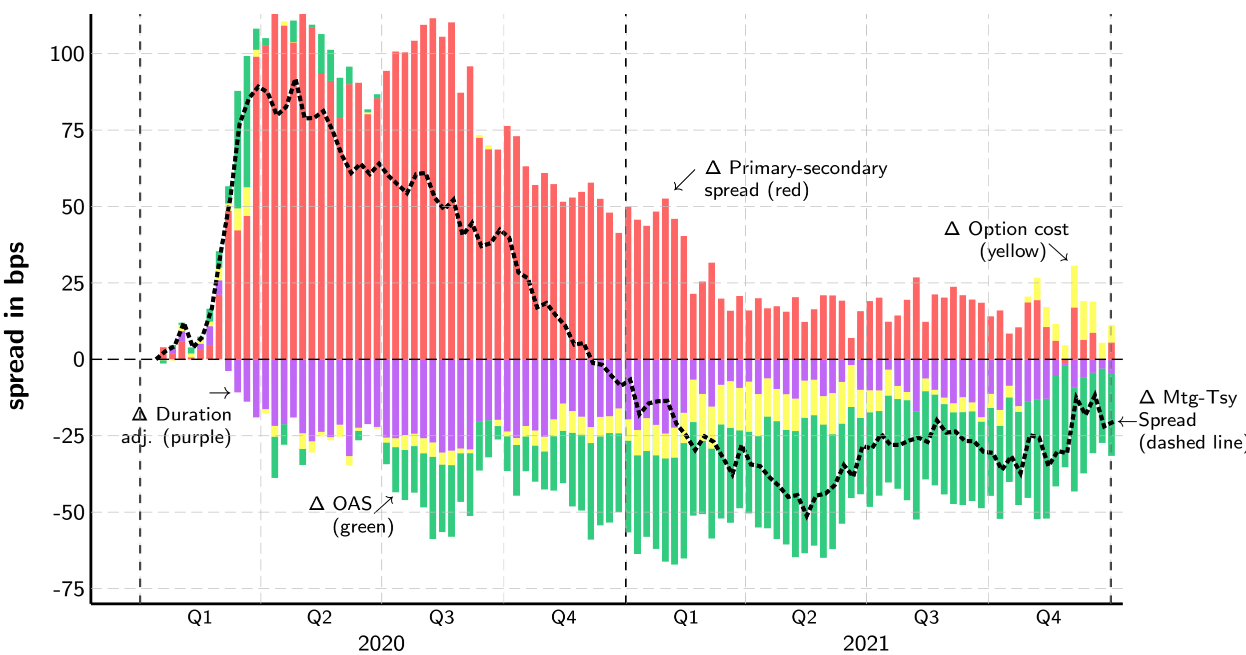


Figure 3: **Measures of intermediation markups.** This figure shows different measures of intermediation markups. The top left is the primary-secondary spread as explained in the text and the top right is gain-on-sale measured as described in Appendix A.1. Both measures are monthly averages constructed using weekly data from Freddie Mac and J.P. Morgan Markets. The bottom left panel uses measures from SEC filings for a selection of publicly-traded mortgage lenders reported in the "Mortgage Profitability: Production and Servicing" table in Inside Mortgage Finance (2023). Values are estimated quarter dummies from a regression of mortgage production income divided by total originations on quarter dummies and a full set of lender fixed effects. Bottom right panel is "Total Net Production Income, Basis Points, Simple Average" from Table B2 of the Mortgage Bankers Association Quarterly Performance Report (QPR).

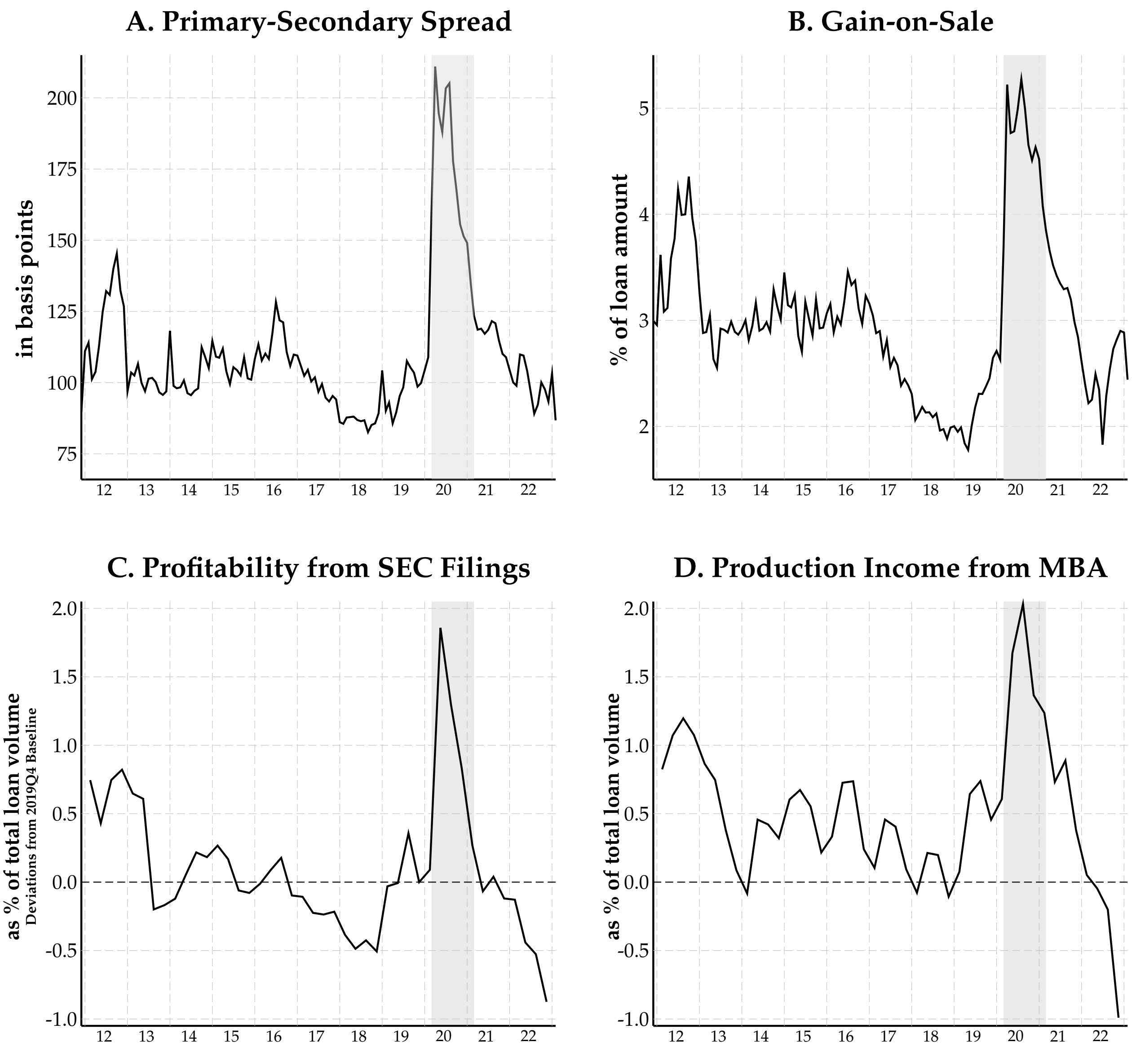


Figure 4: **Intermediation markups and the demand for refinancing.** Numbers next to red squares and green diamonds denote the calendar month in 2020 and 2021, respectively. The trend line and the 90% confidence intervals are estimates using data from 2012-2019. Spreads and gain-on-sale computed based on the methodology described in Section III.C. Data sources: Freddie Mac PMMS; J.P. Morgan Markets; SitusAMC; Mortgage Bankers Association (via Haver Analytics).

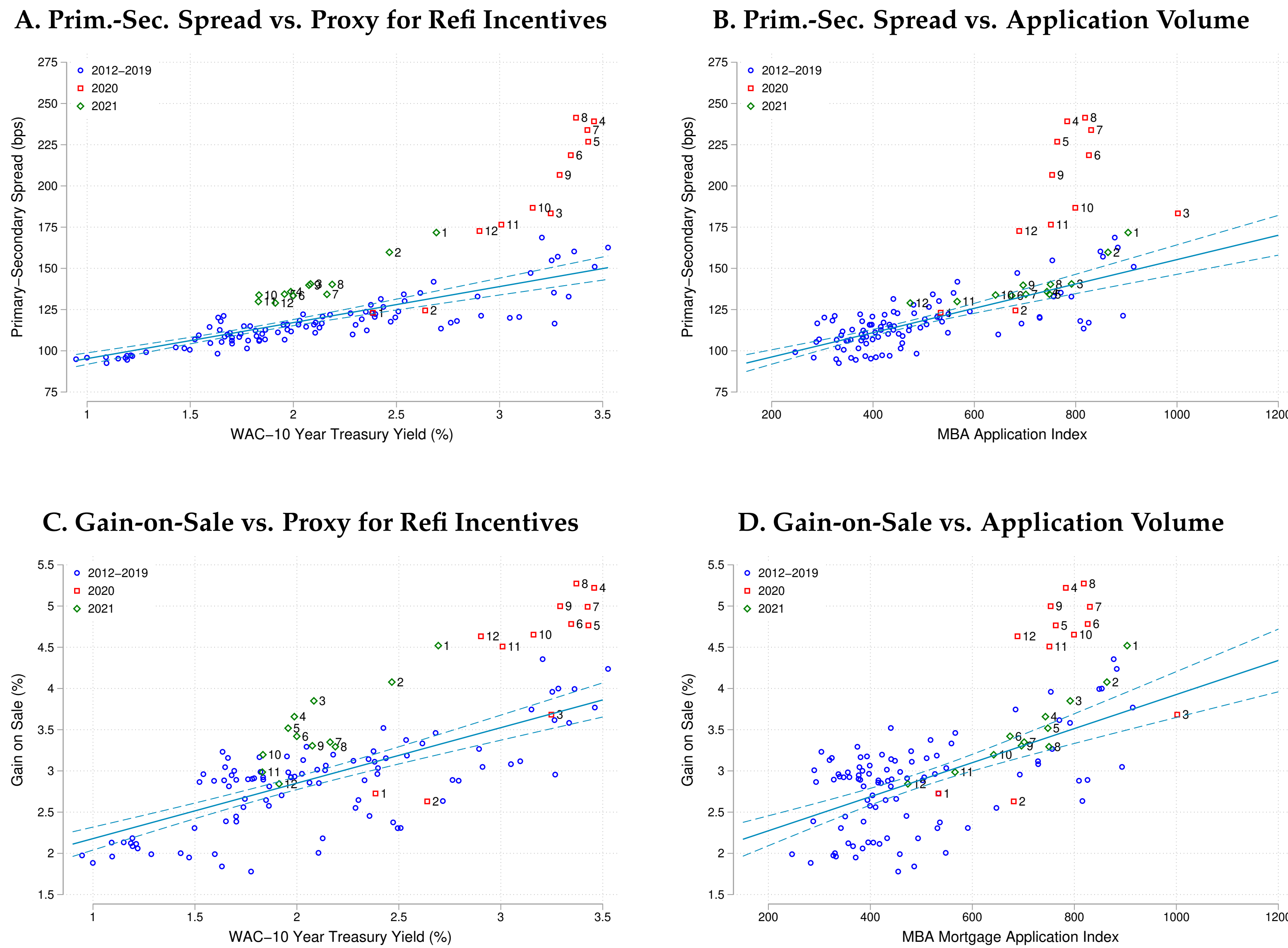
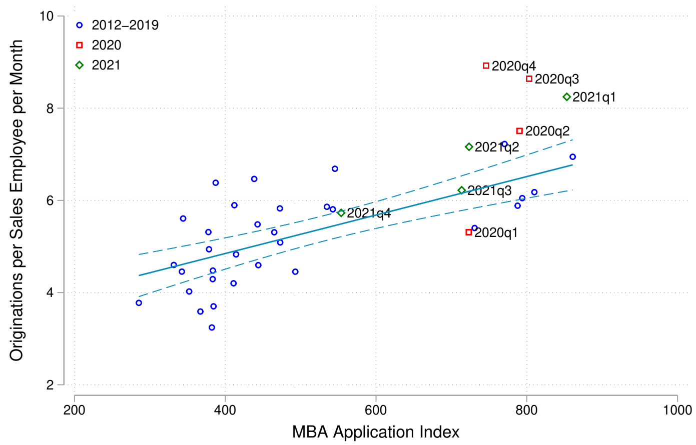
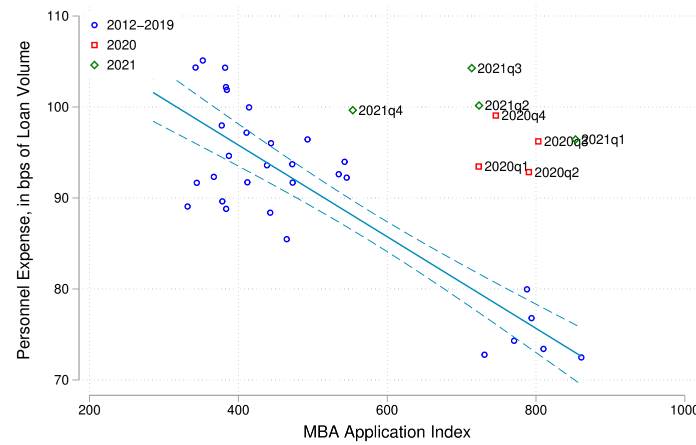


Figure 5: **Loan officer production volume, personnel costs, job postings, and licensing.** Panel A shows the mean monthly originations per sales employee at quarterly frequency from the Mortgage Bankers Association (MBA) Quarterly Performance Report (QPR). Panel B plots sales personnel expenses in basis points of loan volume, also from MBA's QPR. Both Panels A and B show the line of best fit from pre-pandemic observations over 2012-2019. Panel C plots the number of newly issued job postings for loan officers each month, sourced from Burning Glass. Panel D displays the number of newly licensed mortgage loan officers each month (by aggregating NMLS data), as well as the counterfactual number of licenses based on a monthly time-series regression of log(licenses) on two lags of log(applications) and a seasonal dummy for December.

A. Originations Per Sales Employee



B. Personnel Costs (Sales Employees)



C. Job Postings for Loan Officers

D. New Loan Officer Licenses

Figure 6: **Delays in loan closings.** Event study plots showing how mortgage processing times and the incidence of delays to loan closing evolved over 2019-20. Panel A plots coefficients on time dummies from regression of mortgage processing time on application month dummies, loan and borrower characteristics, and CBSA dummies using confidential-use HMDA data. Panel B regresses a dummy for whether there were operational delays affecting loan closing on loan and borrower characteristics and origination month dummies using NSMO data.

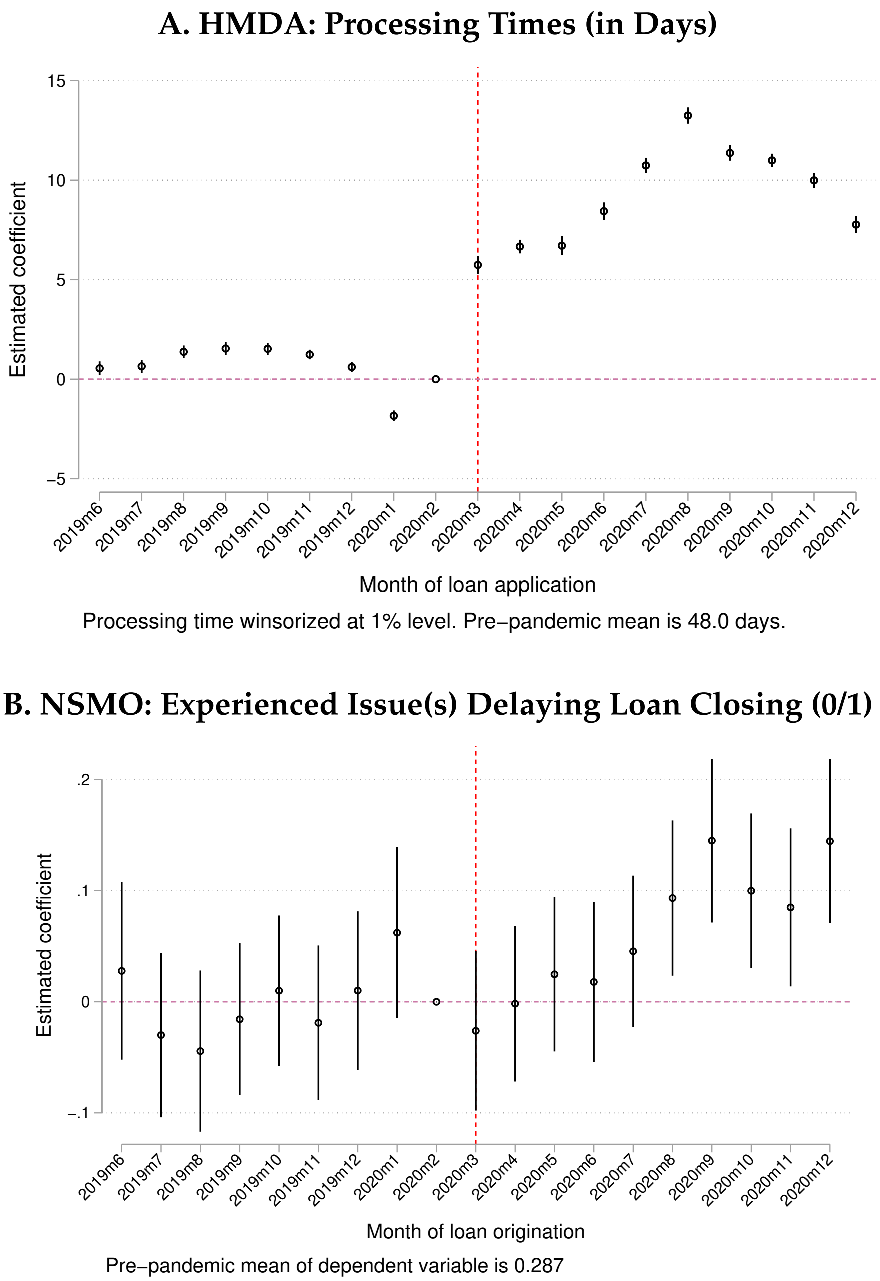
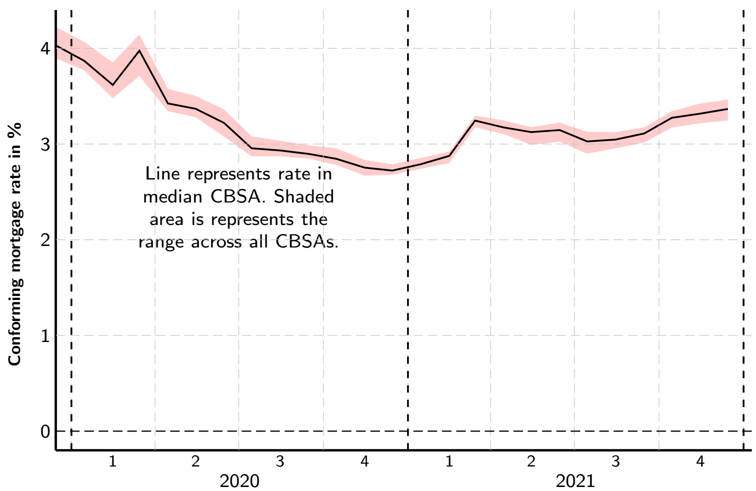
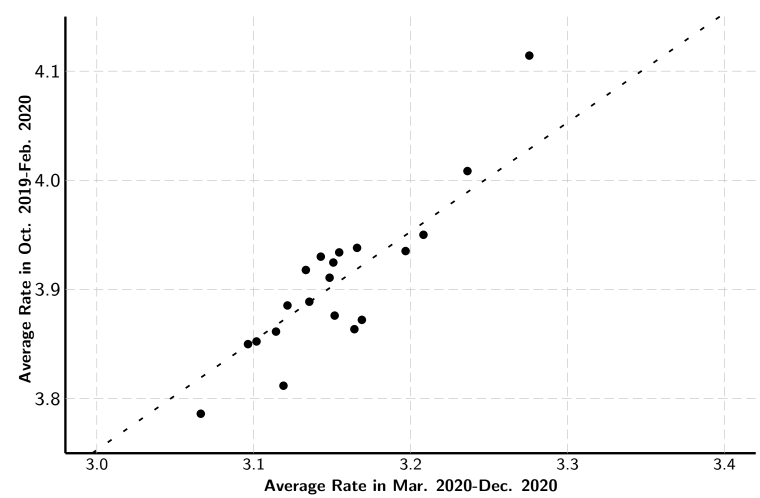


Figure 7: **Dispersion in mortgage rates, application growth, and lender activity across metro areas.** Panels A and B show rates in 20 CBSAs for conforming mortgages with loan amount = $300k, LTV=80, FICO=750, DTI=36 from Optimal Blue Insight data. Panel A shows the time series movements for 20 CBSA. Panel B shows mortgage rates across these CBSAs averaged over the specified time periods. The dashed line in Panel B is a 45 degree line, estimated in a regression where the coefficient on pre-pandemic rates is forced to be 1. Panel C plots the interquartile range of year-over-year growth in mortgage applications measured at the CBSA level in HMDA data, weighted by the number of pre-period mortgage applications in each CBSA. Panel D plots the distribution of the mean and median number of CBSAs in which mortgage originators and mortgage loan officers in HMDA were active.

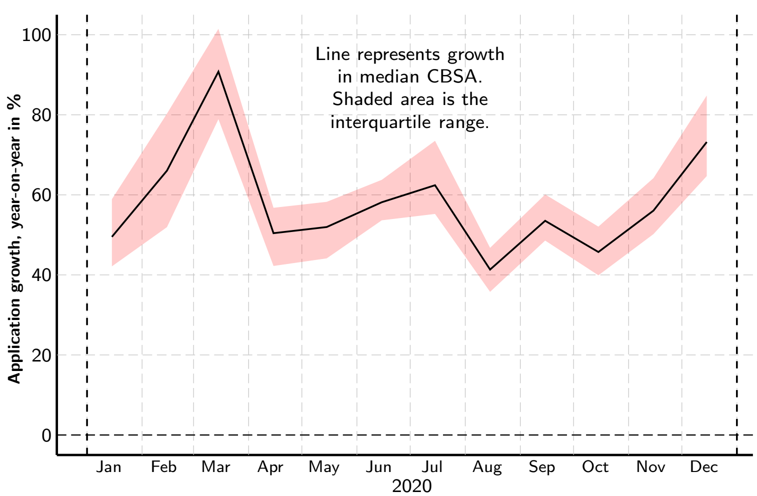
A. Time Series of Mortgage Rates by CBSA



B. Mortgage Rates by CBSA Averaged Over Different Periods.



C. Year-over-year Growth in Mortgage Applications



D. Geographic Coverage

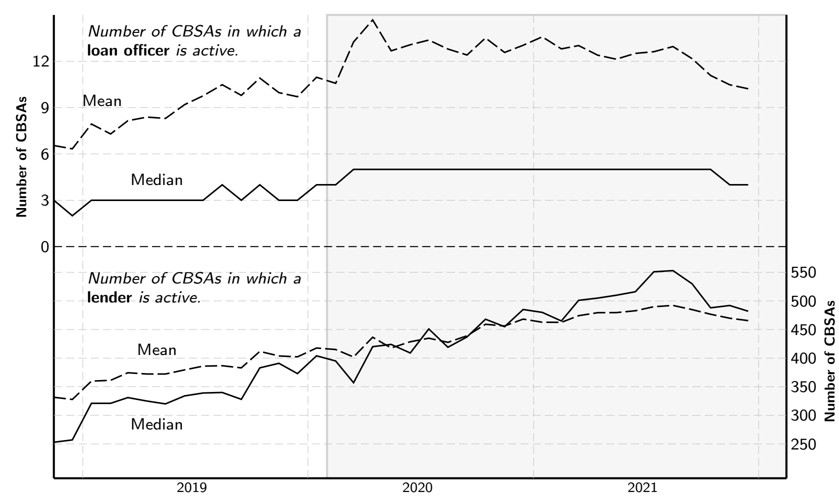


Figure 8: **Nonbank share of conforming market.** Nonbank share of conforming mortgage lending plotted against application date at a weekly frequency, constructed from confidential-use HMDA data. "No controls" plots the raw nonbank share of lending. "Only county FEs" plots the nonbank market share controlling for geography, estimated by regressing a nonbank dummy on time dummies and county dummies, then plotting the estimated time dummies. Similarly, "All controls" plots the nonbank share conditional on a larger set of controls, including dummies for refinancing and cash-out refinancing, log loan amount, log of applicant income, dummies for coapplicant, occupancy, pre-approval, applicant sex, race and ethnicity, DTI, DTI^2, credit score, credit $score^2$, LTV, LTV^2, bins of applicant age, county dummies, and dummies for missing values of each variable. Conforming loans are identified as mortgages that: i) do not exceed the relevant conforming loan limit and ii) are not flagged as government loans. Vertical dashed line indicates the onset of the pandemic, defined as the declaration of a national state of emergency on March 13, 2020.

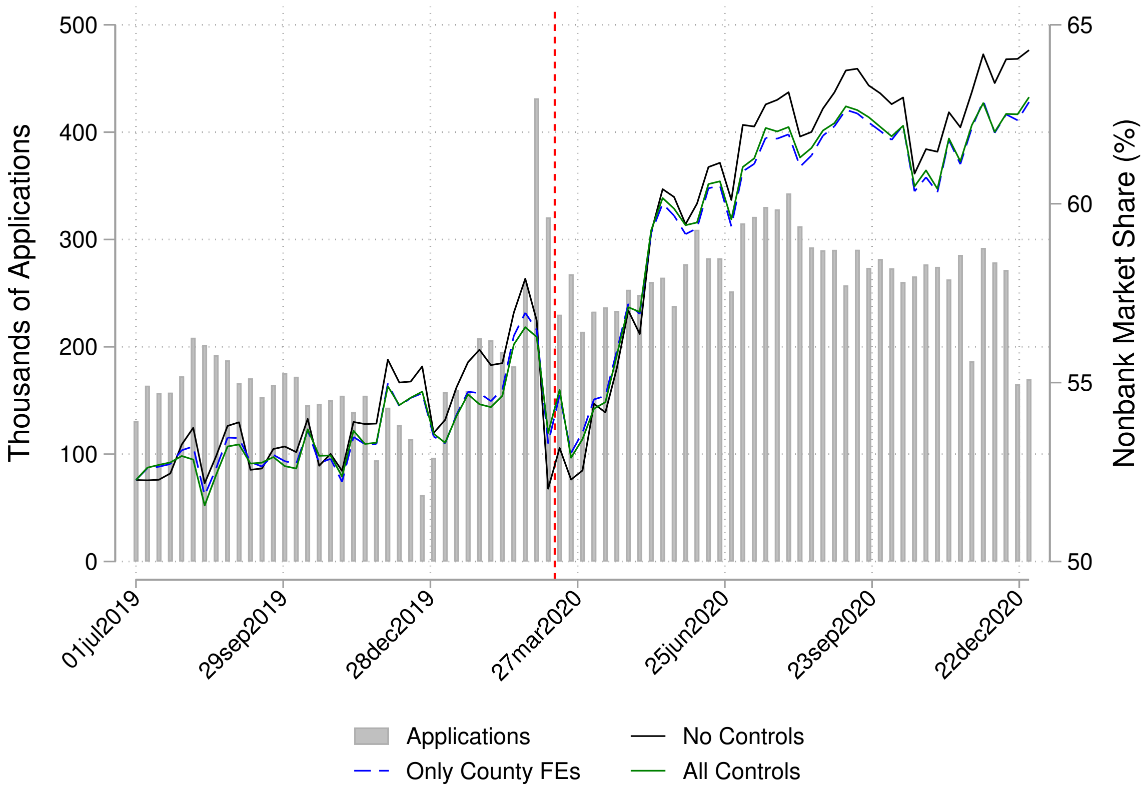


Figure 9: **Default risk and credit supply in the conforming market.** Panel A shows the spread between offered rates for conventional conforming borrowers with credit scores of 680 vs. 750. Panel B shows the spread in locked interest rates between those with scores of 680 vs at least 740. (See Section V.B for details of methodology and controls.) Panel C displays the number of lenders each week posting offered rates for borrowers at or above particular credit score thresholds. Panel D displays the share of loans locked by borrowers at or below score thresholds. The data in Panels A and C come from Optimal Blue Insight, while Panels B and D use lock-level data from Optimal Blue. The vertical line in each panel represents the declaration of a national state of emergency on March 13, 2020.

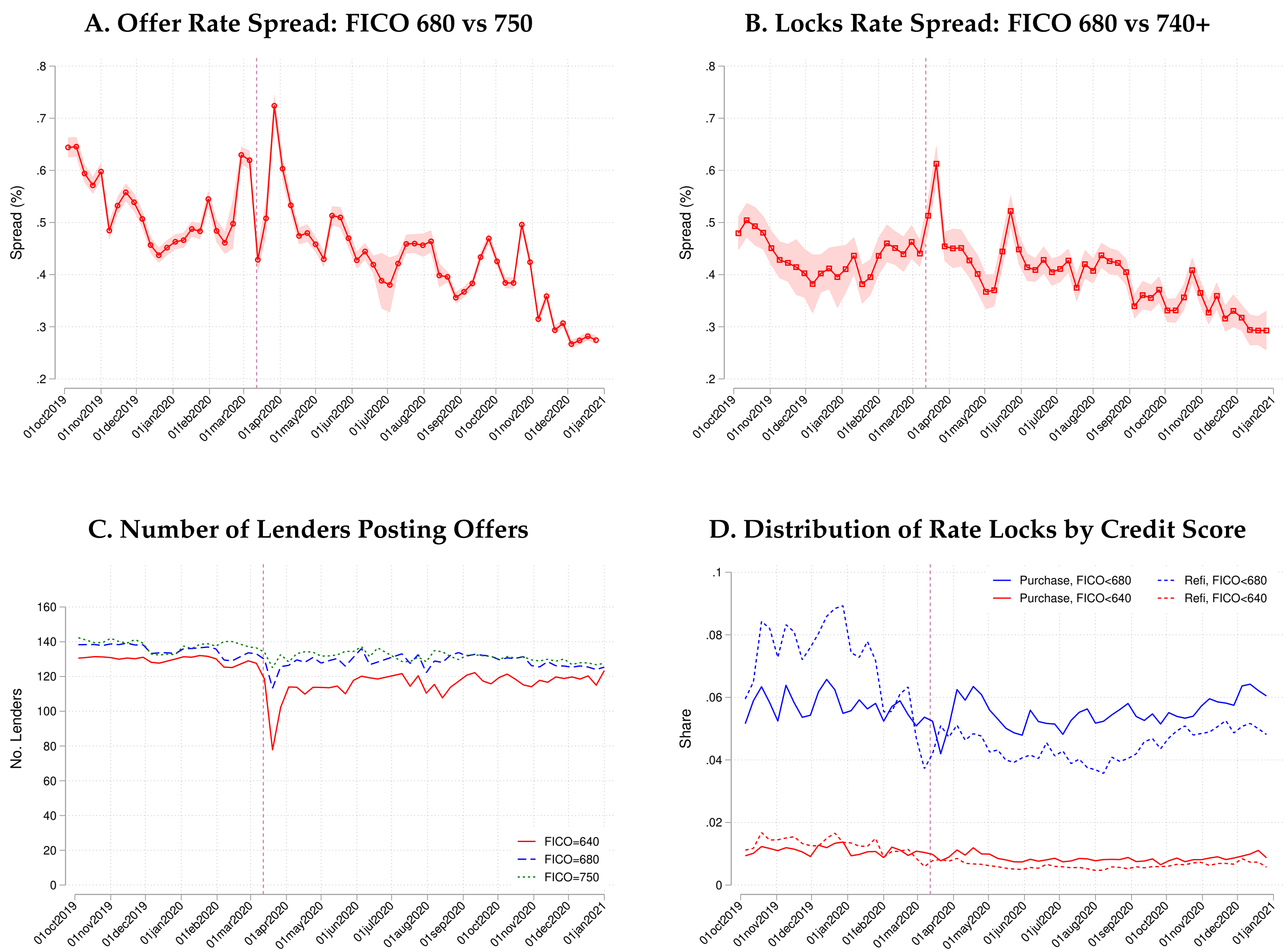


Table 1: **Intermediation Markups and Mortgage Demand.** Data sources: Mortgage Bankers Association (MBA), J.P. Morgan Markets, and Freddie Mac 30-Year Fixed Rate Mortgage Average in the United States [MORTGAGE30US] and Board of Governors of the Federal Reserve System (US) 10-Year Treasury Constant Maturity Rate [DGS10], both retrieved from FRED, Federal Reserve Bank of St. Louis. MBA applications index is a three-week backward-looking moving average. Models include month-of-year dummies (coefficients not displayed). Observations are weekly and include January 2012 through December 2021. Newey-West standard errors (8 lags) in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Primary-Secondary Spread (bp)		Gain-on-Sale ($ per $100 face value)	
	(1)	(2)	(3)	(4)
Mortgage Demand:				
Refi incentive (WAC - 10 Year Treasury)	21.989***		0.668***	
	(2.161)		(0.070)	
MBA Applications Index		0.067***		0.002***
		(0.011)		(0.000)
2020 Dummies:				
March – April	72.848***	77.534***	0.916***	1.129***
	(11.905)	(15.876)	(0.314)	(0.430)
May – June	81.268***	91.195***	1.212***	1.569***
	(4.411)	(5.791)	(0.134)	(0.173)
July – September	81.136***	87.564***	1.334***	1.592***
	(7.025)	(7.186)	(0.152)	(0.178)
October – December	39.618***	39.571***	1.056***	1.124***
	(3.828)	(5.383)	(0.132)	(0.176)
2021 Dummies:				
January – June	28.582***	12.368**	1.005***	0.565***
	(3.751)	(5.060)	(0.102)	(0.146)
July – December	17.849***	4.027	0.313***	-0.069
	(1.918)	(3.226)	(0.095)	(0.119)
Constant	71.577***	86.685***	1.461***	2.021***
	(4.877)	(6.119)	(0.203)	(0.241)
Num obs.	518	517	519	518
Mean of dep. var.	126.76	126.80	3.07	3.07
R^2	0.90	0.85	0.77	0.66
RMSE	9.83	12.21	0.38	0.46
RMSE (no dummies, -Feb. 2020)	8.93	11.29	0.40	0.48

Table 2: **Application Volume and Geographic Dispersion of Lending.** Lender i (loan officer i)-by-month t models estimating the log number of distinct metropolitan areas in which a lender (loan officer) received applications over different phases of 2019 and 2020. Data source: confidential-use HMDA data. Time is indexed by application date. Sample period is January 2019 to December 2020. Omitted dummy is January–August 2019. Standard errors are clustered by lender in columns 1–3 and loan officer in 4–6. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Lender-Level			Loan Officer-Level		
	(1)	(2)	(3)	(4)	(5)	(6)
ln(Total Applications Received$_{i,t}$)	0.343***		0.367***	0.513***		0.500***
	(0.026)		(0.021)	(0.001)		(0.001)
Sept. 2019 – Feb. 2020		0.014***	-0.008*		0.008***	0.002**
		(0.005)	(0.005)		(0.001)	(0.001)
March – April 2020		0.178***	-0.050***		0.282***	0.012***
		(0.017)	(0.012)		(0.002)	(0.001)
May – June 2020		0.170***	-0.025*		0.252***	0.038***
		(0.018)	(0.015)		(0.002)	(0.002)
July – Sept. 2020		0.207***	-0.028*		0.299***	0.043***
		(0.020)	(0.015)		(0.002)	(0.002)
Oct. – Dec. 2020		0.165***	-0.014		0.217***	0.051***
		(0.017)	(0.016)		(0.002)	(0.001)
Num obs.	68,408	68,408	68,408	3,110,173	3,110,173	3,110,173
Mean of dep. var.	5.23	5.23	5.23	1.48	1.48	1.48
SD of dep. var.	1.55	1.55	1.55	1.14	1.14	1.14
Lender FEs	Y	Y	Y	N	N	N
Loan officer FEs	N	N	N	Y	Y	Y

Table 3: **Fintech Lending.** Loan-level linear probability models estimating conditional changes in the fintech share of conventional conforming mortgage lending during the pandemic as well as changes in the difference in mortgage processing time between fintechs and other mortgage lenders. Time is indexed by application date. Sample period is July 2019 to December 2020. Pandemic is defined as the period from March 2020 onwards. Loan controls include dummies for refinancing and cash-out refinancing, log loan amount, log of applicant income, dummies for coapplicant, occupancy, pre-approval, applicant sex, race and ethnicity, DTI, DTI^2, credit score, credit score^2, LTV, LTV^2, bins of applicant age, and dummies for missing values of each variable. Conforming loans are identified as mortgages that: i) do not exceed the relevant conforming loan limit and ii) are not flagged as government loans. Data source: confidential-use HMDA data. Standard errors clustered by county. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	=100 if lender is fintech; 0 otherwise				Processing time (days)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Pandemic	2.65***	1.64***	0.01	-0.18	10.12***	9.20***	9.31***
	(0.15)	(0.17)	(0.14)	(0.15)	(0.13)	(0.15)	(0.15)
Pandemic × FICO<680				2.85***			
				(0.19)			
Fintech					-9.38***	-5.64***	-6.78***
					(0.28)	(0.28)	(0.25)
Pandemic × Fintech					0.85***	1.77***	1.88***
					(0.23)	(0.21)	(0.22)
Num obs.	13,209,832	7,762,129	7,761,406	7,761,406	13,209,832	7,762,129	7,761,406
Mean of dep. var.	16.06	27.34	27.34	27.34	54.65	50.70	50.69
Lenders	All	Nonbank	Nonbank	Nonbank	All	Nonbank	Nonbank
Loan controls	N	N	Y	Y	N	N	Y

Table 4: **Nonbank Share of Lending.** Loan-level linear probability models estimating conditional changes in the nonbank share of conforming mortgage lending over different phases of 2020. Dependent variable = 100 if a loan was originated by a nonbank mortgage company; = 0 otherwise. Time is indexed by application date. Sample period is December 2019 to December 2020. Omitted dummy is for the pre-period from December 2019 to February 15, 2020. Loan controls include dummies for refinancing and cash-out refinancing, log loan amount, log of applicant income, dummies for coapplicant, occupancy, pre-approval, applicant sex, race and ethnicity, DTI, DTI^2, credit score, credit score^2, LTV, LTV^2, bins of applicant age, and dummies for missing values of each variable. Conforming loans are identified as mortgages that: i) do not exceed the relevant conforming loan limit and ii) are not flagged as government loans. Data source: confidential-use HMDA data. Standard errors clustered by county. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Early pandemic [Feb 15-Mar 12]	0.83***	1.50***	1.31***	-0.06	0.77***	2.78***
	(0.22)	(0.15)	(0.15)	(0.30)	(0.20)	(0.17)
Nonbank stress [Mar 13-Apr 30]	-1.27***	0.25	0.11	-1.17***	-0.86***	-0.80***
	(0.20)	(0.16)	(0.15)	(0.27)	(0.19)	(0.17)
Stress easing [May-Dec]	6.84***	6.72***	6.85***	5.23***	3.84***	7.02***
	(0.24)	(0.20)	(0.21)	(0.22)	(0.17)	(0.23)
Num obs.	10,605,218	10,605,206	10,602,575	556,634	1,197,757	8,831,743
Mean of dep. var.	59.85	59.85	59.86	57.41	60.42	51.81
Loan controls	N	N	Y	Y	Y	Y
County dummies	N	Y	Y	Y	Y	Y
Sample restrictions	none	none	none	CS<680	CLTV>90	no fintech

Table 5: **Cross-Sectional Analysis of Nonbank Lending.** Poisson model of the relationship between lending volume and nonbank characteristics over different phases of 2020. Dependent variable is the dollar volume of conforming mortgage lending by lender *i* in week *t*. Time is indexed by application date. Loan volume is aggregated from loan-level confidential-use HMDA data. Lender characteristics are drawn from the nonbank call reports or from HMDA. Sample period is December 2019 to December 2020. Standard errors clustered by originator. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Early Pandemic [Feb 15-Mar 12]:							
× Liquidity ratio	0.12					-0.06	-0.11
	(0.10)					(0.06)	(0.18)
× Capital ratio		0.02				-0.06	-0.20
		(0.07)				(0.06)	(0.26)
× Third-party orig. share			-0.09***			-0.08***	-0.11***
			(0.01)			(0.02)	(0.02)
× Log assets				-0.16***		-0.10***	-0.25**
				(0.03)		(0.03)	(0.10)
× Fintech					-0.22*	-0.17**	-0.12
					(0.12)	(0.07)	(0.08)
Nonbank Stress [Mar 13-Apr 30]:							
× Liquidity ratio	0.27					0.03	0.08
	(0.20)					(0.11)	(0.68)
× Capital ratio		0.11				0.01	0.35
		(0.16)				(0.09)	(0.76)
× Third-party orig. share			-0.20*			-0.18*	-0.21
			(0.11)			(0.11)	(0.13)
× Log assets				-0.09		-0.04	-0.08
				(0.11)		(0.05)	(0.34)
× Fintech					0.21	0.18	0.29
					(0.18)	(0.12)	(0.24)
Stress Easing [May 1-Dec 31]:							
× Liquidity ratio	0.08					0.03	0.05
	(0.11)					(0.06)	(0.50)
× Capital ratio		-0.06				-0.15***	-0.07
		(0.08)				(0.06)	(0.42)
× Third-party orig. share			-0.06			-0.03	-0.03
			(0.04)			(0.04)	(0.05)
× Log assets				-0.08**		-0.12***	-0.19
				(0.04)		(0.04)	(0.23)
× Fintech					0.09	0.19*	0.20
					(0.11)	(0.10)	(0.18)
Num. obs.	19,804	19,804	20,138	19,804	20,274	19,798	1,521
Mean of dep. var.	84.13	84.13	83.17	84.13	82.65	84.16	620.97
Lender & month FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender sample	All	All	All	All	All	All	Assets > $1bn

Table 6: **Metro Area Differences in Conventional Conforming Mortgage Rates (%).** Mortgage lock-level regression of interest rate (adjusted for discount points and credits) on area characteristics and loan characteristics, including loans locked from November 2019 to August 2020 in the 100 largest CBSAs, with the exception of (4) and (9), which include locks from late February to August 2020, due to data availability. COVID cases per 1,000 are lagged one month. The top 4 lenders' market share, HHI, year-over-year unemployment, time spent at workplaces, and failed lender share are all standardized to have a mean of 0 and standard deviation of 1. Mortgage interest rates are adjusted for points paid by borrower (credits received from lender) using daily data from Optimal Blue Insight on offered interest rates for loans with different net points. Additional controls include CBSA-level fixed effects (county-level fixed effects in (4), (7), and (9)), as well as lock week interacted with: binned FICO score, binned loan-to-value ratio, interest rate type (fixed-rate, 5/1 ARM, 7/1 ARM, or 10/1 ARM), and loan purpose (purchase vs. refinance). Data Sources include Optimal Blue locks data, *New York Times* COVID data, Bureau of Labor Statistics unemployment data, confidential-use HMDA data, failed lender market share from Buchak and Jørring (2024), and county-level Google COVID-19 Community Mobility Reports data from the Opportunity Insights Tracker. Standard errors in parentheses, clustered at CBSA level for (1)–(3), (5)–(6), and (8) and at the county level for (4), (7), (9). ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Virus spread:									
COVID cases per capita	-0.0032***								
	(0.0008)								
Dummy: MSA in top quartile		-0.0178***						-0.0184***	-0.0177***
		(0.0051)						(0.0050)	(0.0039)
Unemployment:									
Year-over-year change in U.R.			0.0112**					0.0146***	0.0157***
			(0.0054)					(0.0049)	(0.0032)
Mobility:									
Time at Workplaces				0.0217***					0.0115**
				(0.0058)					(0.0055)
Market concentration:									
COVID × top 4 share					0.0025				
					(0.0042)				
COVID × HHI						0.0048			
						(0.0042)			
COVID x failed lender share							-0.0082***	-0.0115***	-0.0168***
							(0.0023)	(0.0028)	(0.0027)
Num obs.	1,130,086	1,130,086	1,130,086	915,233	1,130,086	1,130,086	1,118,397	1,118,398	905,708
Mean of dep. var.	3.33	3.33	3.33	3.21	3.33	3.33	3.33	3.33	3.21
Geographic FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan controls x week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Internet Appendix: How Resilient Is Mortgage Credit Supply? Evidence from the COVID-19 Pandemic

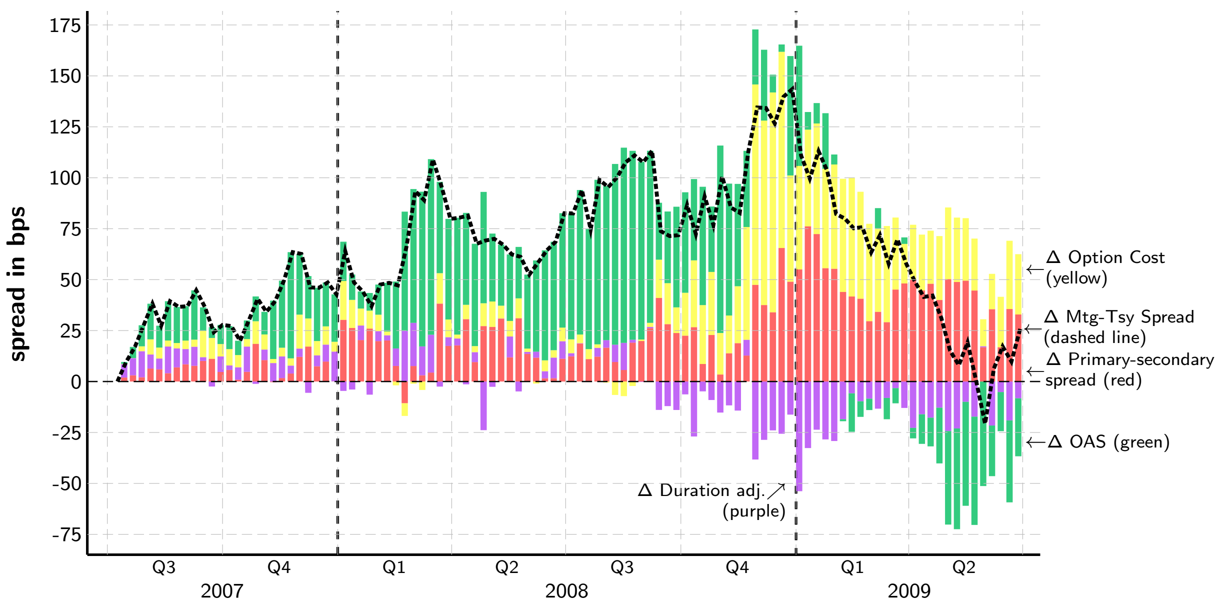
Andreas Fuster, Aurel Hizmo, Lauren Lambie-Hanson,
James Vickery and Paul Willen

A Additional Evidence on Rates and Markups in the Conforming Market

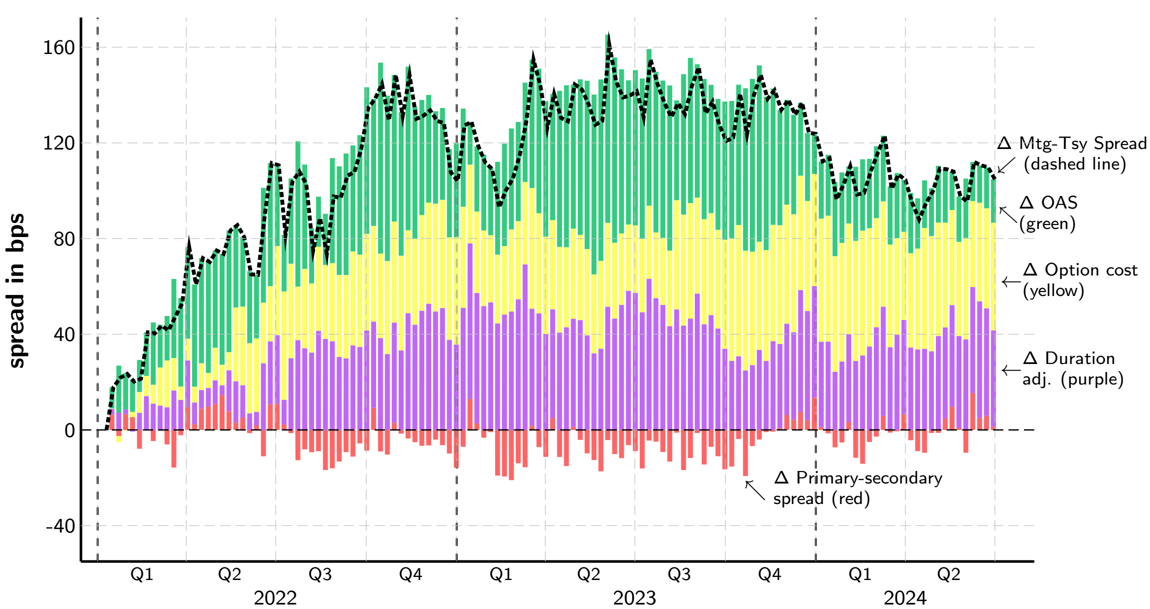
Figure A.1: **OAS measures from different dealers**. OAS is calculated by interpolating values between the two MBS coupons on either side of the net note rate as described in Section III.A.1. Data sources: Freddie Mac PMMS, J.P.Morgan Markets, Citi.

Figure A.2: **Tracing the mortgage-Treasury spread — other episodes.** This figure decomposes the mortgage-Treasury spread into four components, based on the methodology described in Section III.A. The black dashed line shows the change in spread between the headline mortgage rate (from PMMS) and 10-year Treasury yields relative to the beginning of each episode, in basis points. Data sources: Freddie Mac PMMS, Optimal Blue, J.P. Morgan Markets.

A. Global Financial Crisis (2007-2009)



B. Monetary Tightening Cycle (2022-2024)



A.1 Details on the Gain-on-Sale Calculation

A.1.1 Formal Treatment

Consider a mortgage with initial balance S_0 and a mortgage rate r_p. Let r_s be the yield on an MBS containing mortgages with note rate r_p, and g be the guarantee fee paid to the GSEs. If we assume that time is continuous and the loan has a constant prepayment hazard λ_p, the value of the loan is:

$$V(r_p - g) = \int_0^\infty e^{-r_s t} S_t \left(r_p - g + \lambda_p\right) dt = S_0 \frac{r_p - g + \lambda_p}{r_s + \lambda_p}. \tag{6}$$

where the second equality follows from the fact that with a constant prepayment hazard, $S_t = S_0 e^{-(\lambda_p)t}$. Equation (6) implies that the value of the mortgage, all else equal, is increasing in the note rate and decreasing in the g-fee and the MBS yield, as one would expect. Prepayment speed, λ_p, appears in both the numerator and the denominator and its effect is therefore ambiguous. Taking the derivative of equation (6) with respect to λ_p yields

$$\frac{\partial V}{\partial \lambda_p} = -\frac{(r_p - g - r_s)}{(r_s + \lambda_p)^2} S_0.$$

Intuitively, if $r_p - g - r_s$ is positive, investors are receiving cash flow in excess of their funding costs (or outside investment opportunity, which is r_s if they invest in MBS) and would like to delay prepayment as long as possible. In general, $r_p - g - r_s$ is positive at origination and thus newly originated loans with lower prepayment speeds fetch a higher valuation in the market. For seasoned loans, $r_p - g - r_s$ can be negative (if market yields increased since origination), in which case higher prepayment speeds lead to higher valuations.

To compute gain-on-sale, we assume the lender can sell the loan in the MBS market for V. Then, using equation (6), gain-on-sale as a share of the loan amount can be expressed as

$$\frac{V(r_p - g) - S_0}{S_0} = \frac{r_p - r_s - g}{r_s + \lambda_p}. \tag{7}$$

Equation (7) omits two components that are important in actual gain-on-sale calculations. First, lenders typically value the servicing flow s separately from the rest of the cash flow. The net servicing income flow is $s(1 - c_s)$, where c_s is the cost of servicing as a share of servicing income. Second, the lender typically collects points and fees at origination, which we denote as F, so the initial cash outlay is not S_0 but $S_0 - F$.[1] Taking those two

[1] F is net of loan-level price adjustments (LLPAs) paid to the GSE when selling the loan.

factors into account, we can write gain-on-sale as

$$\underbrace{\pi}_{\text{Gain-on-Sale}} = \underbrace{\frac{V(r_p - g - s) - S_0}{S_0}}_{\substack{\text{(1) Secondary Market} \\ \text{Income}}} + \underbrace{s \cdot \frac{1 - c_s}{r_s + \lambda_p}}_{\substack{\text{(2) Mortgage} \\ \text{Servicing Right} \\ \text{(MSR)}}} + \underbrace{\frac{F}{S_0}}_{\substack{\text{(3) Points} \\ \text{and Fees}}} . \tag{8}$$

$\frac{1-c_s}{r_s+\lambda_p}$ is known as the servicing multiple.

A.1.2 Empirical Implementation

Our approach to implementing equation (8) follows the principles established in Fuster, Lo, and Willen (2024).

For our baseline estimates, we assume r_p equals the Freddie Mac PMMS 30-year conforming rate for the time period in question. In Figure A.3, we compare those estimates with estimates using the rates from the MBA weekly application survey and the Optimal Blue Insight data. Specific details of our calculations are described below:

1. For Secondary Market Income (component (1)), we compute $V(r_p - g - s)$ as follows. s and g are 25bp and 42bp, respectively, following Fuster et al. (2013). "TBA" stands for "to be announced," representing the MBS market where new agency mortgages are typically forward-sold (see Vickery and Wright, 2013). Given that MBS coupons are at 50bp intervals, interpolation between the two nearest MBS coupons is necessary to price a specific loan. For instance, if $r_p - g - s$ is 3.25%, the equal-weighted average price of a 3.0 coupon and a 3.5 coupon is taken. Further, as in Fuster et al. (2024), we assume that settlement happens 45 days later and use a weighted combination of prices on one-, two-, and three-month-out TBA contracts.

2. To compute the value of the MSR (component (2)), our challenge is to find empirical values for $\frac{1-c_s}{r_s+\lambda_p}$, the servicing multiple. To do this, we use data from SitusAMC, an independent valuation service company. These multiples are derived from transaction values of brokered bulk MSR deals, market participant surveys, and a pricing model, encapsulating the net value of servicing accounting for the income flow value minus expected costs.[2] The multiples are provided to us at monthly frequency at the coupon-by-loan type (GSE versus FHA) level. Figure A.4 shows the evolution of these multiples for conventional conforming and FHA segments. Multiples for given fixed coupons decreased over time, reflecting the drop in market interest rates. However, the interpolated multiple at the typical coupon rate for new loans decreased only modestly before fully reverting over the course of 2020.[3]

[2] Fuster et al. (2013) calculate a measure of gain-on-sale called "OPUC," where they explicitly consider the choice of coupon into which a loan is securitized but for the most part assume constant multiples over time. In Appendix A.2, we show that results using OPUC are qualitatively similar.

[3] Our estimates could overstate gain-on-sale if the SitusAMC servicing multiples fail to properly reflect the

3. Finally, for each of our rate series, we construct a corresponding time series for Points and Fees (component (3)). Freddie Mac, in addition to collecting rate information, also gathered Points and Fees data from lenders—although they discontinued this practice at the end of 2022, which is after our period of interest. The Mortgage Bankers Association application data also include points and fees. For the Optimal Blue Insight data, we use their cross-sectional rate-point combinations to construct a time series with a constant level of points. We subtract a Loan-Level Price Adjustment (LLPA) paid to Fannie Mae and Freddie Mac for our baseline mortgage of 50bp and we further include the 25bp surcharge that FHFA imposed on refinances delivered to Fannie Mae and Freddie Mac after December 1, 2020.

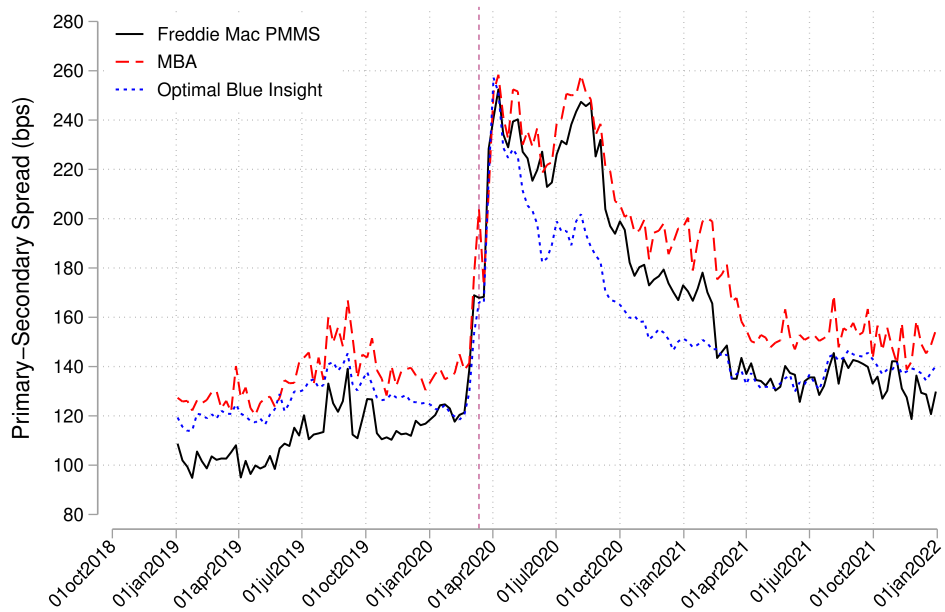
Although the calculations are similar, for their baseline estimates, Fuster, Lo, and Willen (2024) use a different r_p series created using proprietary TPO rate sheet data, different servicing multiples, and by subtracting a 100bp rebate (which can be thought of as their calculation not including origination charges paid by borrowers). As a result, for the overlapping period, their estimates in levels are different but the intertemporal patterns are very similar.

Finally, our treatment of FHA loans is identical to what is described above, except that s and g are 44bp and 6bp, respectively, and no LLPAs are imposed.

risks for servicers of elevated forbearance and non-payment. But in Section V.B we show there is no evidence of a rising interest rate premium for high-risk conventional conforming loans during the pandemic, which speaks against this hypothesis. We also have no reason to doubt that the SitusAMC valuations internalize the risks of forbearance; in fact, given secondary market illiquidity for MSRs, transactions may understate going-concern values if they mainly reflect forced sales at fire-sale prices. Finally, even if we set the servicing multiple to zero—a very extreme assumption—this would reduce gain-on-sale by only about $1, still not bringing it fully in line with historical patterns.

Figure A.3: **Intermediation markups in the conforming market.** Primary-secondary spread (Panel A) and gain-on-sale (Panel B) measured based on the methodologies described in Sections III.A.1 and III.C, respectively. Data sources: Freddie Mac PMMS, Optimal Blue, J.P. Morgan Markets, MBA (via Haver Analytics). Vertical line represents the declaration of a national state of emergency on March 13th, 2020.

A. Primary-Secondary Spread



B. Gain-on-Sale

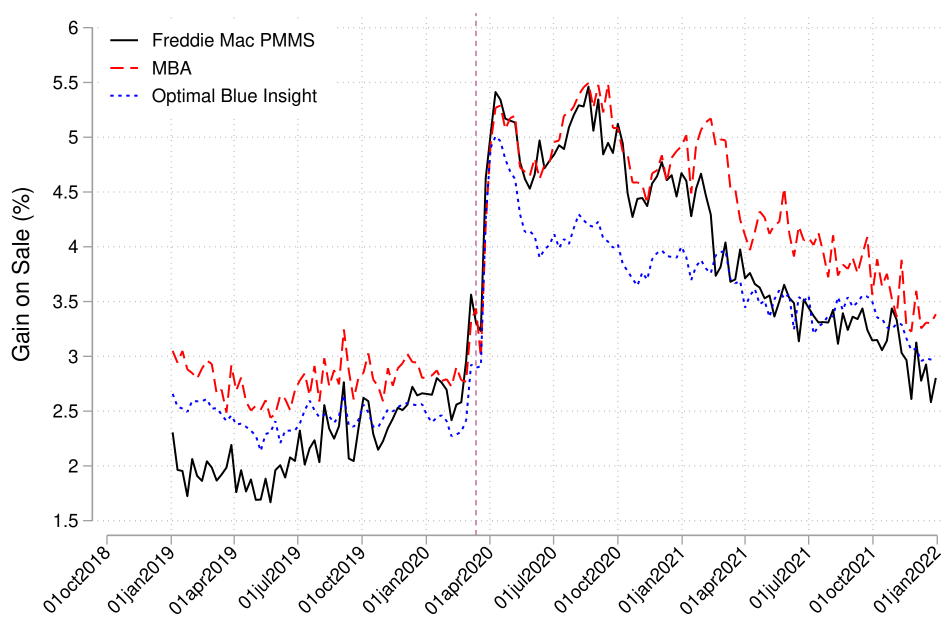
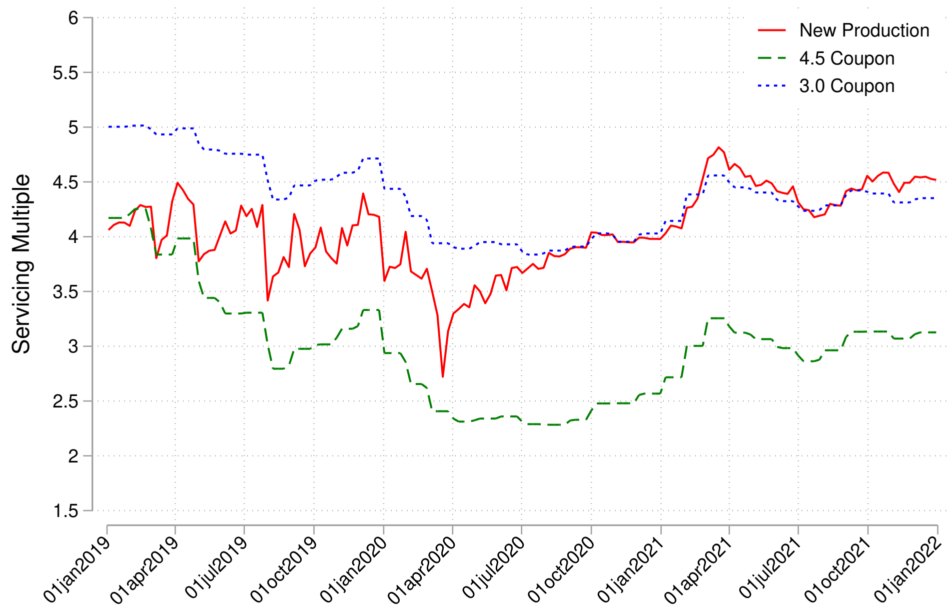
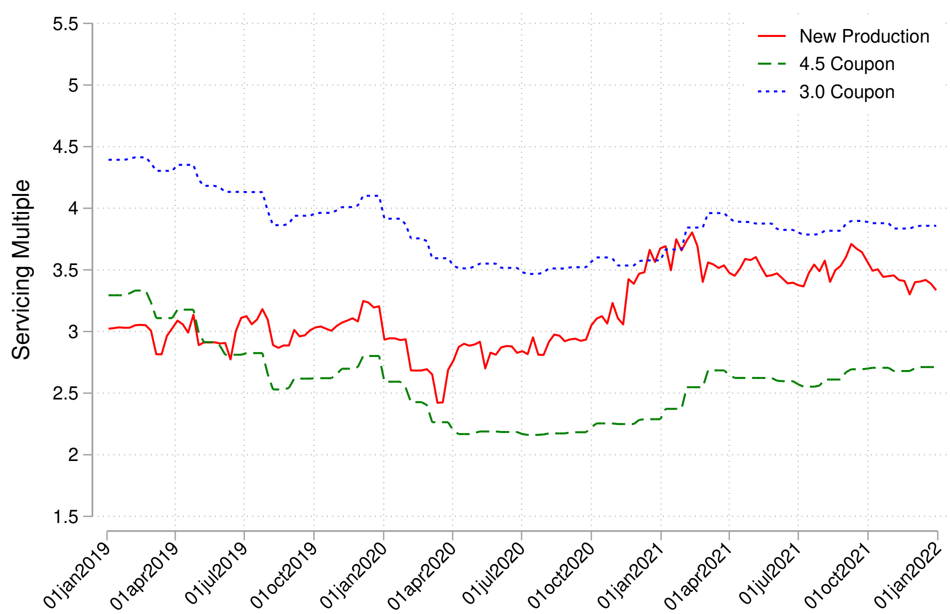


Figure A.4: **Base servicing multiples for conforming and FHA mortgages.** "New Production" interpolates between specific coupons (two examples of which are shown) to obtain servicing multiples for a loan originated at the primary market mortgage rate adjusted for discount points. Data sources: SitusAMC for servicing multiples; Freddie Mac PMMS (Panel A) and MBA (Panel B) for mortgage rates.

A. Conforming Mortgages



B. FHA Mortgages



A.2 OPUC Measure of Intermediation Markups

Figure A.5: **Evolution of originator profits and unmeasured costs (OPUC)**. Data source: https://www.newyorkfed.org/research/epr/2013/1113fust.html. Vertical line represents the declaration of a national state of emergency on March 13, 2020.

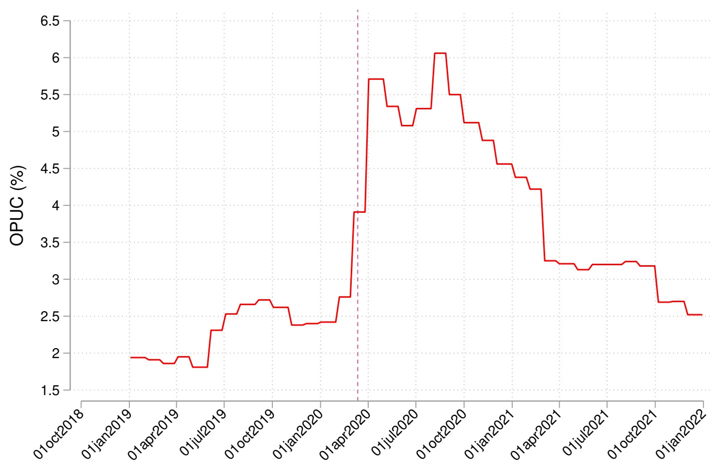
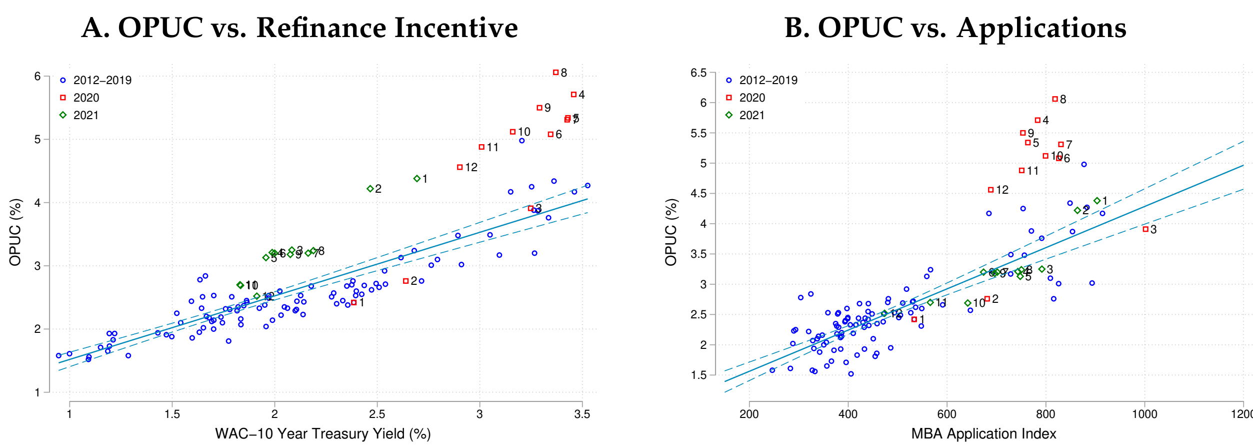


Figure A.6: **OPUC and mortgage demand.** Data sources: Freddie Mac PMMS; for OPUC: https://www.newyorkfed.org/research/epr/2013/1113fust.html; Mortgage Bankers Association (via Haver Analytics).



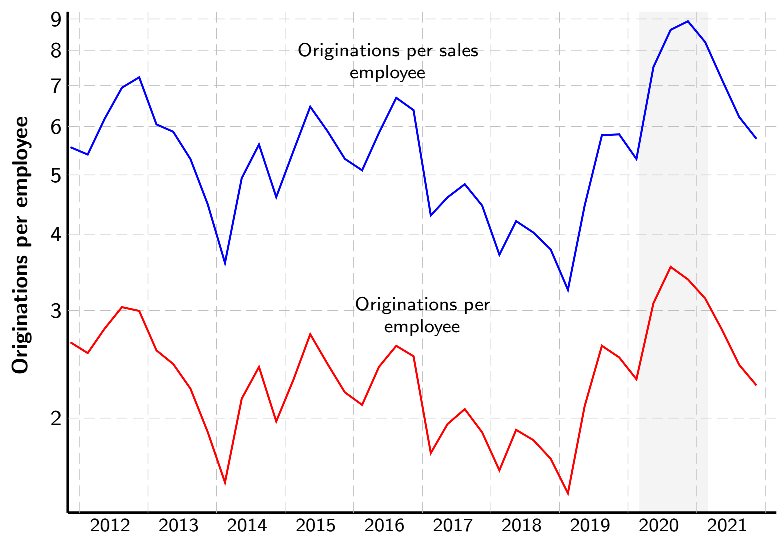
B Additional Evidence on Capacity Constraints

Table A.1: **Time-Series Model of License Issuance.** Monthly time-series regression of log(licenses) on lags of log(applications) and a seasonal dummy for December. License issuance is drawn from the NMLS; mortgage applications are from the Mortgage Bankers Association. Newey-West standard errors with 3 lags in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Excluding Pandemic Period		Including Pandemic Period	
	(1)	(2)	(3)	(4)
L.ln(applications)	-0.122	-0.090	-0.159	-0.109
	(0.080)	(0.079)	(0.130)	(0.118)
L2.ln(applications)	0.259**	0.242**	0.282**	0.169
	(0.113)	(0.107)	(0.126)	(0.149)
L3.ln(applications)		0.051		-0.070
		(0.112)		(0.139)
L4.ln(applications)		-0.045		0.263
		(0.096)		(0.183)
December	-0.292***	-0.289***	-0.231***	-0.275***
	(0.032)	(0.033)	(0.062)	(0.057)
Pandemic			-0.218*	-0.281**
			(0.125)	(0.125)
N	59	57	69	67
Mean Y	8.6	8.6	8.6	8.6
SD Y	0.136	0.13	0.17	0.17
Adj. R2	0.33	0.39	0.21	0.35
Months included	Apr. 2015-Feb. 2020	June 2015-Feb. 2020	Apr. 2015-Dec. 2020	June 2015-Dec. 2020

Figure A.7: **Originations per employee – further evidence.** Panel A shows the mean monthly originations per sales employee and per (total) employee using Mortgage Bankers Association Quarterly Performance Report data. Panel B shows the personnel costs for non-sales employees as a share of dollars originated, captured each quarter from 2012 to 2021.

A. Originations per Employee (Sales and Non-Sales Employees)



B. Personnel Costs (Non-Sales Employees)

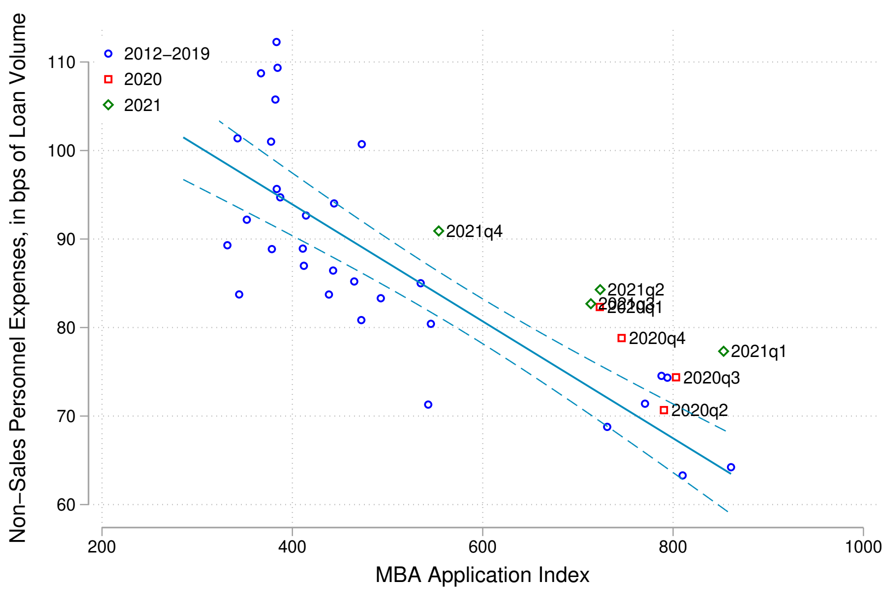


Figure A.8: **Median processing times and application volumes: 2012-2021.** Data source: confidential-use HMDA data and Mortgage Bankers Association (MBA Application Index). Time is indexed by application date. Processing time is calculated for originated loans only.

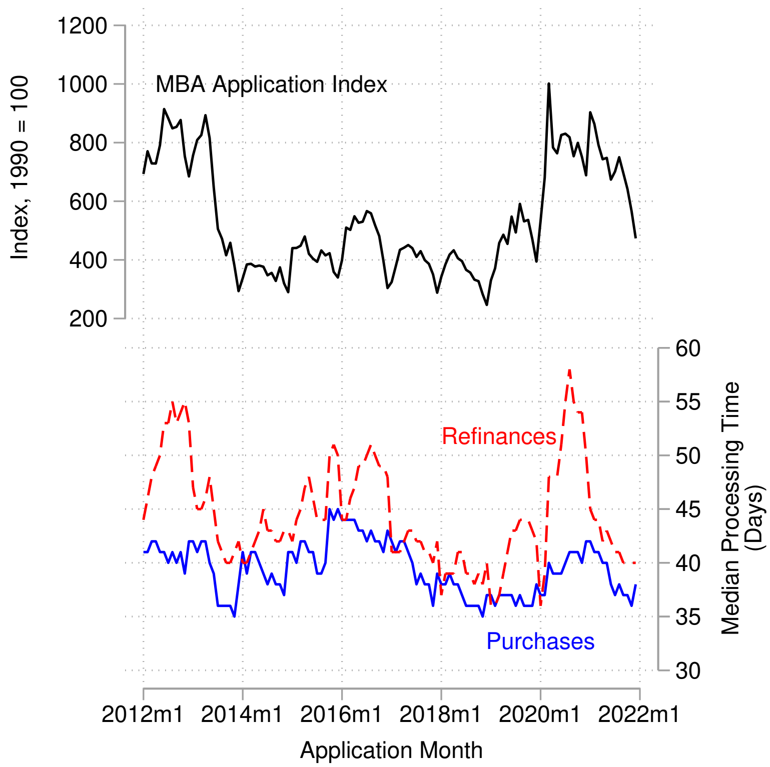
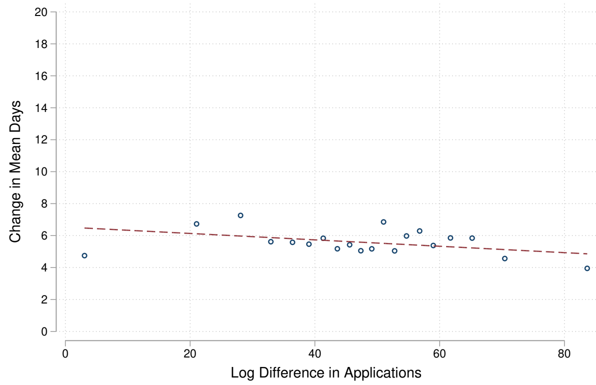
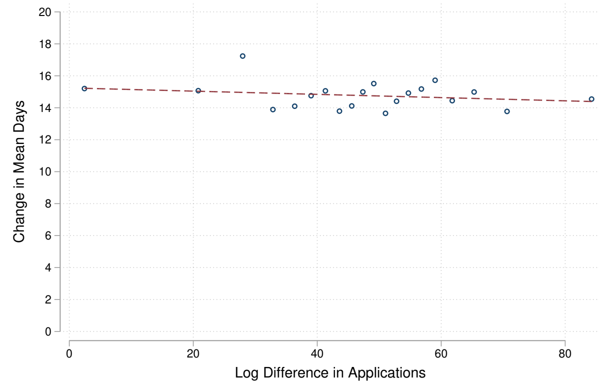


Figure A.9: **CBSA-level application growth, loan processing time increases, and rate declines.** Binned scatterplot of CBSA-by-month, year-over-year log difference in mortgage applications from confidential-use HMDA data, displayed against mean processing time (in winsorized days) in Panels A and B and against mean decline in zero-discount-point interest rates from Optimal Blue Insight data in Panel C. All panels display data for March-December 2020, controlling for calendar month.

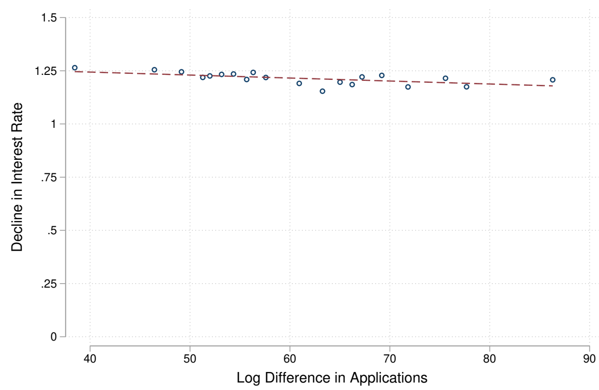
A. Purchase mortgage processing time



B. Refinance processing time



C. Decline in mortgage rates



C Additional Evidence on Fintech Lending

C.1 Fintech Processing Speed Over Time

This section contains evidence supporting Section IV.D examining how the processing-speed advantage of fintech lenders relative to other nonbanks has evolved over time.

We run the following linear model using loan-level confidential-use HMDA data:

$$\text{ProcessingTime}_i = \beta_t \text{Fintech}_i + \gamma_{ct} + \Gamma X_i + \varepsilon_i \tag{9}$$

where ProcessingTime_i is the difference between the action date and application date (in calendar days) for originated loans recorded in HMDA, and the estimates of interest are the elements of β_t, a vector of coefficients on month dummies interacted with a dummy for whether the originator is a fintech lender based on the classification in Jagtiani et al. (2021). Controls include month $\times$ CBSA dummies (γ_{ct}) and X_i, which is a vector of loan and borrower characteristics that mimics the set of controls in Table 3 of Fuster et al. (2019); we control for log(loan amount), log(applicant income), a pre-approval dummy, and indicators for occupancy status, property type, applicant gender and coapplicant status, as well as dummy variables for missing values of the above variables. Time is indexed by application month. Standard errors are double clustered by lender and month.

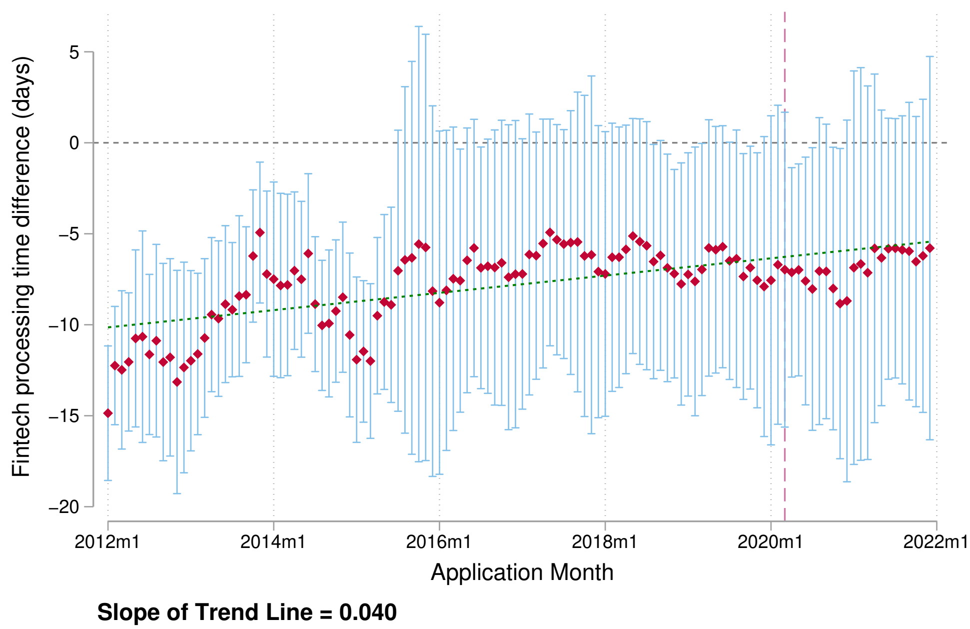
We restrict the sample to conventional conforming mortgages, defined as mortgages below the relevant local conforming limit, which are not flagged as government mortgages (e.g., FHA or VA loans), because our focus is the conforming market and because mortgage processing and underwriting procedures vary across conforming, government, and jumbo loans. We further restrict the sample to originations by nonbanks; this creates a more "apples-to-apples" comparison because banks and nonbanks differ on other dimensions aside from technology, including regulation, funding, and diversification across business lines. We estimate separate models for purchase mortgages and refinances given that the relationship between processing time and borrower characteristics may be different between the two types of loans.

Dynamic estimates of conditional differences in processing times between fintechs and other nonbanks are reported in Figure A.10. Throughout the sample period, fintech lenders typically process mortgages faster, although the advantage of these firms has diminished over time. Specifically, based on the trendlines, fintech processing speeds were about 10-12 days faster in 2012-13, similar to estimates in Fuster et al. (2019). Over the period from 2012-21, however, this "fintech advantage" declined by roughly 0.5 days per year (0.04 days per calendar month, which is the trend line slope reported in the figure) for purchase mortgages and 0.55 days per year (0.046 days per month) for refinances.

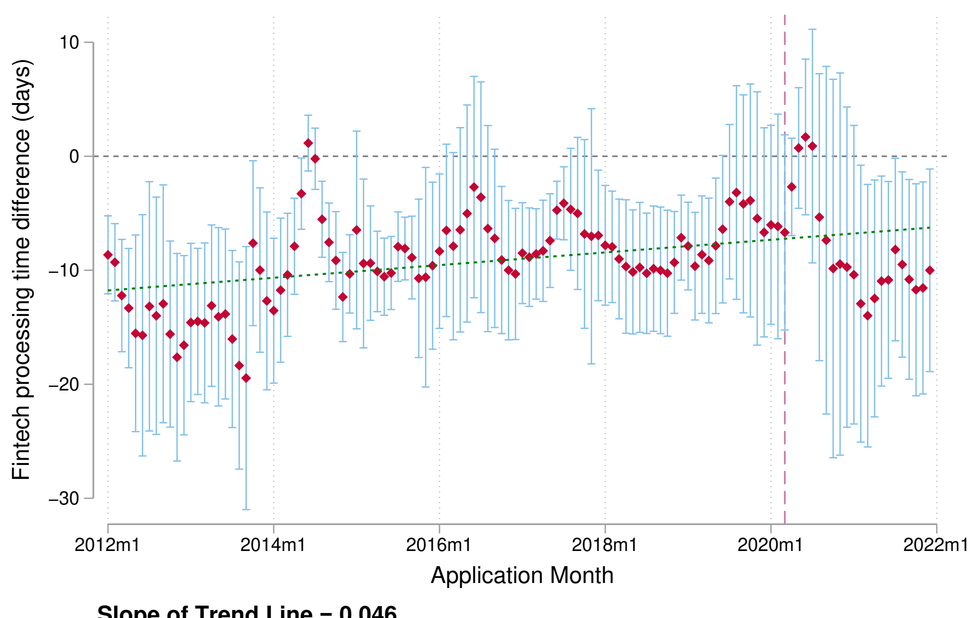
Fintech processing was however still about 6-7 days faster than other nonbanks as of late 2019 and early 2020 just before the pandemic, consistent with the argument that fintechs retain a technological advantage over other nonbanks despite the broader diffusion of online lending.

Figure A.10: **The evolution of the processing time advantage of fintech lenders.** Figure shows the difference in processing time (in days) between fintech lenders and other nonbanks conditional on loan and borrower controls. Each point on the graph reports the coefficient on the fintech dummy (along with corresponding 95% confidence levels) from a loan-level linear model of processing time estimated separately month-by-month from January 2012 to December 2021 using confidential-use HMDA data and conditioning on the controls from Table 3 of Fuster et al. (2019). We estimate results separately for purchase mortgages and refinances, and restrict the sample to conventional conforming first-lien mortgages. Fintech lenders classified by the Jagtiani et al. (2021) classification. Dashed vertical line is March 2020.

A. Purchase mortgages



B. Refinances



C.2 Fintech Market Shares and Processing Times by Loan Purpose

Figure A.11: **Evolution of fintech market share of nonbank lending.** Monthly coefficients and 95% confidence intervals showing the fintech share of nonbank conventional conforming mortgage lending. Based on regressions of a fintech originator dummy on time dummies and loan and geographic controls like the specification in column (3) of Table 3, but with monthly dummies instead of a single pandemic dummy (using January 2020 as the base category). Time is indexed by mortgage application date. Standard errors clustered by county.

(a) Purchase Mortgages (b) Refinances

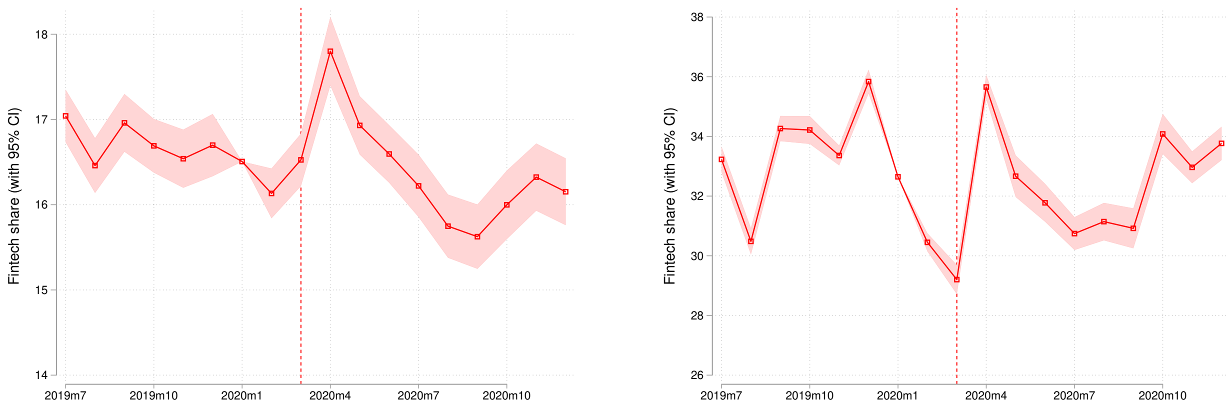


Table A.2: **Fintech Lending by Loan Purpose.** This table repeats the analysis from Table 3 after restricting the sample first to purchase mortgages and then to refinances. Linear probability models estimating conditional changes in the fintech share of conforming mortgage lending during the pandemic as well as changes in the difference in mortgage processing time between fintechs and other mortgage lenders. Time is indexed by application date. Sample period is July 2019 to December 2020. Pandemic is defined as the period from March 2020 onwards. Loan controls include dummies for cash-out refinancing, log loan amount, log of applicant income, dummies for coapplicant, occupancy, pre-approval, applicant sex, race and ethnicity, DTI, DTI^2, credit score, credit $score^2$, LTV, LTV^2, bins of applicant age, and dummies for missing values of each variable. Conforming loans are identified as mortgages that: i) do not exceed the relevant conforming loan limit and ii) are not flagged as government loans. Data source: confidential-use HMDA data. Standard errors clustered by county. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

A. Purchase Mortgages

	=100 if lender is fintech; 0 otherwise				Processing time (days)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Pandemic	0.58***	-0.23*	-0.22*	-0.34***	4.09***	4.02***	3.52***
	(0.07)	(0.09)	(0.10)	(0.10)	(0.13)	(0.18)	(0.18)
Pandemic × FICO<680				1.55***			
				(0.20)			
Fintech					-6.80***	-6.05***	-6.11***
					(0.37)	(0.48)	(0.47)
Pandemic × Fintech					-0.32	-0.25	-0.30
					(0.30)	(0.33)	(0.33)
Num obs.	4,362,054	2,446,561	2,446,183	2,446,183	4,362,054	2,446,561	2,446,183
Mean of dep. var.	9.26	16.51	16.51	16.51	50.08	48.98	48.98
Lenders	All	Nonbank	Nonbank	Nonbank	All	Nonbank	Nonbank
Loan controls	N	N	Y	Y	N	N	Y

B. Refinances

	=100 if lender is fintech; 0 otherwise				Processing time (days)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Pandemic	1.81***	-0.74***	-0.15	-0.37	12.66***	12.56***	13.73***
	(0.18)	(0.21)	(0.21)	(0.22)	(0.23)	(0.18)	(0.17)
Pandemic × FICO<680				3.27***			
				(0.29)			
Fintech					-10.65***	-4.33***	-5.23***
					(0.29)	(0.21)	(0.20)
Pandemic × Fintech					0.02	0.11	0.24
					(0.29)	(0.25)	(0.25)
Num obs.	8,847,778	5,315,568	5,315,223	5,315,223	8,847,778	5,315,568	5,315,223
Mean of dep. var.	19.42	32.32	32.32	32.32	56.90	51.49	51.48
Lenders	All	Nonbank	Nonbank	Nonbank	All	Nonbank	Nonbank
Loan controls	N	N	Y	Y	N	N	Y

D Additional Evidence on Nonbank Financial Constraints

Figure A.12: **Share of third-party originations.** Share of third-party originations in the conforming mortgage market plotted against application date, constructed using confidential-use HMDA data. Conforming loans are identified as mortgages not larger than the relevant conforming loan limit that are not flagged as government loans. Third-party originations are measured based on a HMDA indicator variable for whether the borrower on a given loan submitted their application through a third party rather than directly to the lender. Vertical line indicates the onset of the pandemic, defined as the declaration of a national state of emergency on March 13, 2020.

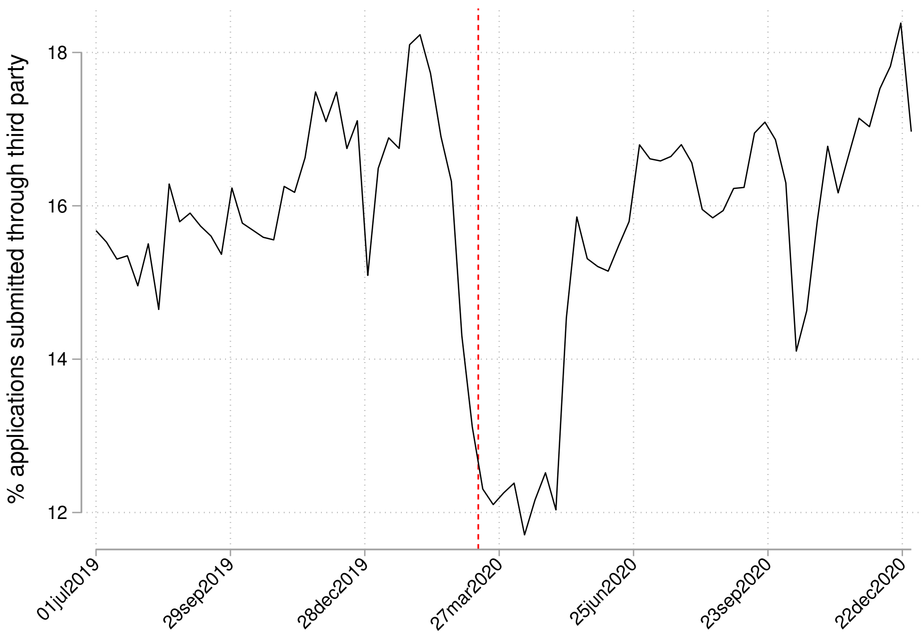


Table A.3: **Nonbank Share of Lending: Effect of Controlling for Third-Party Channel.** Loan-level linear probability models showing conditional changes in the nonbank share over different phases of 2020. Column 1 reproduces column 3 from Table 4, while column 2 uses the same specification but includes a third-party-origination dummy as an additional control. Time is indexed by application date. Sample period is December 2019 to December 2020. Data source: confidential-use HMDA data. Standard errors clustered by county. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
Early pandemic [Feb 15-Mar 12]	1.31***	1.80***
	(0.15)	(0.16)
Nonbank stress [Mar 13-Apr 30]	0.11	0.90***
	(0.15)	(0.15)
Stress easing [May-Dec]	6.85***	6.93***
	(0.21)	(0.20)
Num obs.	10,602,575	10,602,575
Mean of dep. var.	60	60
Loan controls	Y	Y
County dummies	Y	Y
Channel dummy	N	Y

Figure A.13: **Nonbank market share: jumbo loans.** Nonbank share of jumbo mortgage lending plotted against application date, constructed using confidential-use HMDA data. "No controls" plots the raw nonbank share of lending. "Only county FEs" plots the nonbank market share controlling for geography, estimated by regressing a nonbank dummy on time dummies and county dummies, then plotting the estimated time dummies. Similarly, "All controls" plots the nonbank share conditional on a larger set of controls, including dummies for refinancing and cash-out refinancing, log loan amount, log of applicant income, dummies for coapplicant, occupancy, pre-approval, applicant sex, race and ethnicity, DTI, DTI^2, credit score, credit $score^2$, LTV, LTV^2, bins of applicant age, county dummies, and dummies for missing values of each variable. Jumbo loans are identified as mortgages that i) exceed the relevant conforming loan limit and ii) are not flagged as government loans. Vertical line indicates the onset of the pandemic, defined as the declaration of a national state of emergency on March 13, 2020.

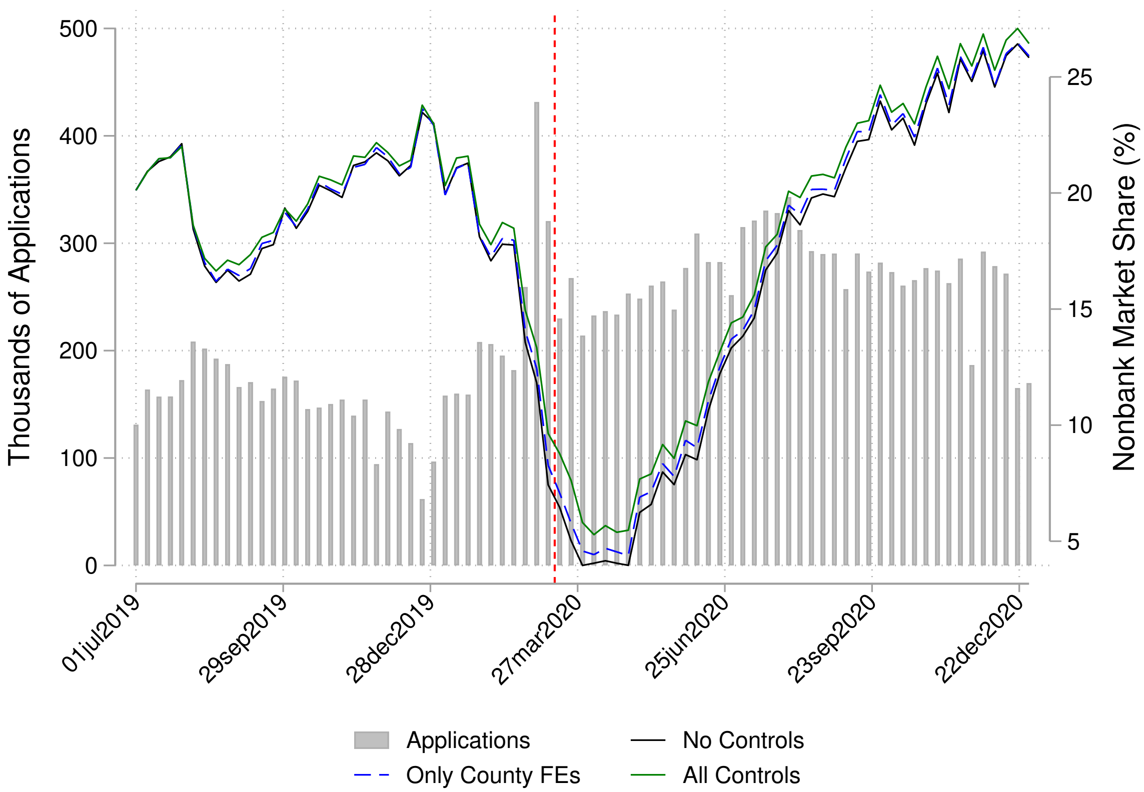
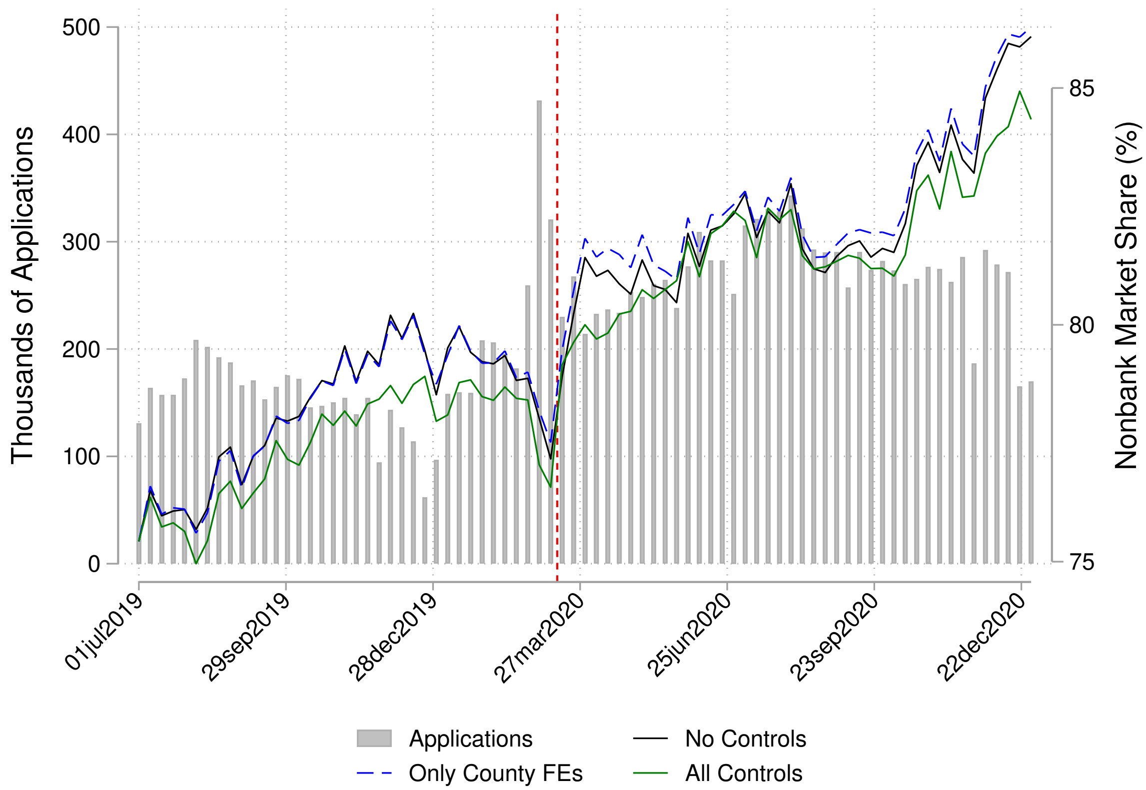


Figure A.14: **Nonbank market share: government loans.** Nonbank share of government mortgage lending (e.g., FHA, VA) plotted against application date, constructed using confidential-use HMDA data. "No controls" plots the raw nonbank share of lending. "Only county FEs" plots the nonbank market share controlling for geography, estimated by regressing a nonbank dummy on time dummies and county dummies, then plotting the estimated time dummies. Similarly, "All controls" plots the nonbank share conditional on a larger set of controls, including dummies for refinancing and cash-out refinancing, log loan amount, log of applicant income, dummies for coapplicant, occupancy, pre-approval, applicant sex, race and ethnicity, DTI, DTI^2, credit score, credit score^2, LTV, LTV^2, bins of applicant age, county dummies, and dummies for missing values of each variable. Vertical line indicates the onset of the pandemic, defined as the declaration of a national state of emergency on March 13, 2020.



E Additional Evidence on Competition and Shopping

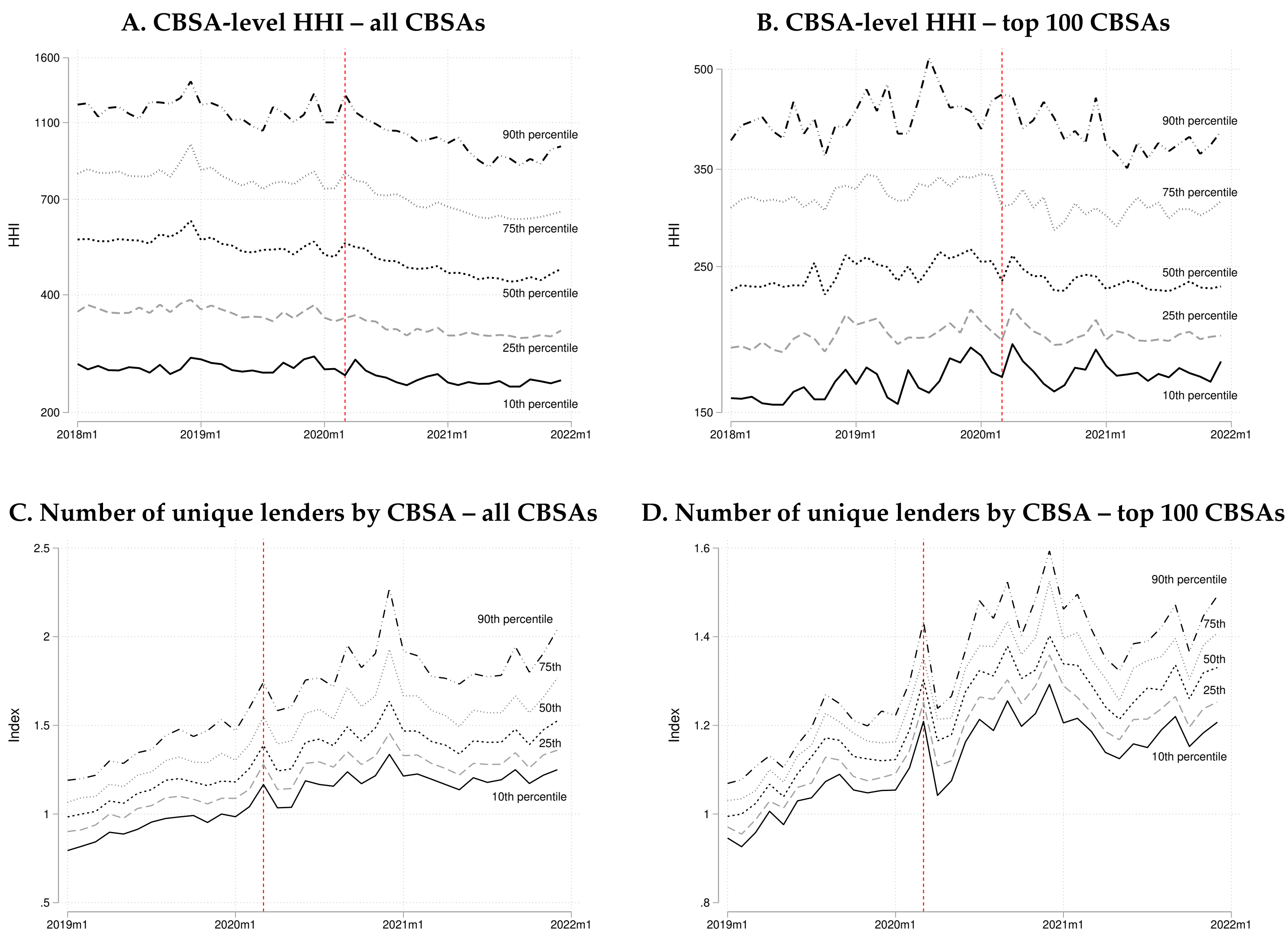
E.1 Did Market Concentration Increase During the Pandemic?

Panel A of Figure A.15 shows the distribution of monthly HHIs of originated mortgages calculated at the CBSA-application month level. The y-axis uses a log-scale. Panel B presents the same data but restricted to the top 100 most populous CBSAs. While there is considerable variation in the amount of concentration between the 10th and 90th percentile CBSA, all markets feature a large number of lenders, and there is a decline in concentration during the pandemic period.

Panels C and D plot the number of unique lenders that receive at least one application from a borrower in a given CBSA in a given month, relative to the number of unique lenders in the same CBSA in the same calendar month in 2018. (For example, the data point in Jan 2020 is the number of unique lenders in a CBSA in Jan 2020 divided by the number of unique lenders in a CBSA in Jan 2018.) Panels A and C use all 926 CBSAs in the data, while Panels B and D focus on the top 100 CBSAs by population. Both panels show that, with the exception of a short dip in April and May 2020, the number of unique lenders serving each CBSA increased during 2020, building on an existing trend of a greater number of unique lenders serving each CBSA.

To summarize, these charts show that the local market concentration of lenders tended to *decrease* during the pandemic period, when measured in terms of metro area-level Herfindahl-Hirschman Indices for lenders or the number of unique lenders serving each metro.

Figure A.15: **Evolution of market concentration and number of active lenders.** These plots display the 10th, 25th, 50th, 75th, and 90th percentile values of two measures: a CBSA-by-month-level HHI calculation of lender concentration (Panels A and B, which use a log-scale on the y-axis) and the number of unique lenders (HMDA reporters) taking applications in a CBSA each month (Panels C and D). Panels A and C include all CBSAs, while B and D include the 100 most populous CBSAs. The red vertical line in each panel indicates the onset of the pandemic, defined as the declaration of a national state of emergency in March 2020. Data sources: confidential-use HMDA and Census 2018 5-Year American Community Survey.



E.2 Did Mortgage Shopping Behavior Change During the Pandemic?

One possible driver of higher markups during the pandemic could be a reduction in prospective borrowers' search activity, giving lenders higher effective pricing power. In this section, we test this hypothesis by examining data on borrower search and shopping from the National Survey of Mortgage Originations (NSMO) and from Google Trends. This analysis supports our discussion of lender market power and shopping in Section V.D.

E.2.1 NSMO Evidence

The NSMO is a quarterly survey of borrowers with newly originated closed-end first-lien residential mortgages in the United States, undertaken by the Federal Housing Finance Agency and the Consumer Financial Protection Bureau. The nationally representative survey inquires about borrowers' experiences getting a mortgage, their perceptions of the mortgage market, and their future expectations. The survey collection began in 2014, and in most quarters, the data include between 1,000 and 1,900 responses.

We use the most recent public version of the data, released in July 2024 and covering loan originations through 2021.[4] We focus on loans originated during the period from mid-2019 through end-2020. Since we do not know a borrower's application date, we consider loans originated from April 2020 onward as being potentially affected by the pandemic (given a typical time lag between application and origination of around two months).

To study shopping behavior, we consider six outcome variables:

1. A dummy for whether a borrower indicates that they "seriously considered" more than one mortgage lender/broker before choosing where to apply for their mortgage.

2. A dummy for whether a borrower indicates that they applied to more than one mortgage lender/broker, *and* that they did so because they were searching for better loan terms.

3. An index of information use across different sources, standardized to have a mean 0 and standard deviation of 1.[5]

4. A dummy for whether a borrower indicates that having a local office or branch nearby was important in choosing the mortgage lender/broker they used.

[4]The data are available at `https://www.fhfa.gov/nsmodata`.

[5]Specifically, we sum the answers to the "x08" questions ("How much did you use each of the following sources to get information about mortgages or mortgage lenders?"), where "A lot" gets a score of 2, "A little" a score of 1, and "Not at all" a score of 0. The information sources are: your lender or mortgage broker; other mortgage lenders/brokers; real estate agents or builders; material in the mail; websites that provide information on getting a mortgage; newspaper/TV/radio; friends/relatives/co-workers; bankers, credit unions or financial planners; and housing counselors.

5. A dummy for whether a borrower indicates that having a paperless online mortgage process was important in choosing the mortgage lender/broker they used.

6. A dummy for whether a borrower indicates that having used the mortgage lender/broker previously to get a mortgage was important for their choice.

The first two variables are perhaps the most "direct" measures of mortgage shopping. The third one provides a composite indicator of information search and use. The remaining three are more indirect measures, but ones that could potentially be affected by the pandemic—perhaps borrower preferences shifted toward local lenders, lenders with a strong online presence, or those that they have dealt with before. Any such shifts could indicate a change in the relative market power of affected lenders.

We regress each of these variables on a set of month dummies (with March 2020 as the omitted base category) as well as a large set of controls for borrower and loan characteristics.[6] Results are shown in Figure A.16. As discussed below, we find no overall evidence of a decline in search intensity, and in fact on most dimensions, there is little hard evidence of significant shifts in shopping behavior during the pandemic period. Specifically:

- For the "considered multiple lenders" and "applied to multiple lenders in search of better loan terms" outcome variables, we notice a slight negative trend during the pre-COVID period; this can potentially be explained by the fact that shopping activity generally tends to decrease as rates fall, as shown by Bhutta et al. (2024). However, this downward trend stops after March 2020, and, if anything, borrowers become *more* likely again to consider or apply to multiple lenders.

- We do not see any changes in the intensity of information use.

- There is no increased preference for local lenders, except perhaps for loans originated in April 2020 (although even for this month, the coefficient estimate is not statistically significant and is lower than during two months in the 2019 pre-period). From June 2020 onward, the preference for local lenders tends to be lower than it was pre-pandemic, even though the difference is not statistically significant.

- Perhaps surprisingly, there is only weak evidence of a shift toward an increasing preference for a paperless online process. The coefficients in 2020 are higher than in 2019, although there is some evidence of a pre-trend in that values were already higher in January and February of 2020, prior to the onset of the pandemic. That said, in a regression where the month dummies are replaced with a single COVID-period dummy equal to 1 from April 2020 onward, the coefficient on this dummy is positive with a p-value of 0.055 for the "paperless online process = important" outcome.

[6] The controls are listed in the notes of Figure A.16. Note that the only control that qualitatively affects the results is the loan purpose dummy, as shopping behavior differs between purchase and refinance loans, and the share of these loan purposes shifted over our sample period.

- Finally, borrowers' preferences for using a lender they had previously done business with weakens over the course of 2020. Employing the same test as above, the difference between the average pre- vs post-pandemic value for "prior relationship = important" is negative, with a p-value of 0.064.[7]

To summarize, we find no evidence from this analysis of NSMO data that borrowers searched less intensively, although there is some evidence that the pandemic reduced the value borrowers put on using a lender they had previously done business with, a change that if anything should *enhance* competition. This finding is also consistent with evidence from Black Knight (2020) that "servicer retention", that is, the share of borrowers refinancing through their existing servicer, fell to unusually low levels during the pandemic.

E.2.2 Google Trends

Google Trends data on borrower internet search activity provides another measure of shopping intensity. We construct a composite index of search volume by averaging searches for the terms "mortgage rate," "mortgage refinance," "mortgage lender," "refinance cost," and "mortgage cost".

Panel A of Figure A.17 shows that searches for these terms spiked in March 2020 to levels far above any month going back to 2012. Search activity remained elevated until late 2021.

Panel B tests whether borrower search activity was also unusually high relative to what would be predicted based on the level of refinance incentives, measured by the WAC-10-year spread as in our earlier analysis. We find a positive relationship between search volume and the refinancing incentive, and that borrower search activity was unusually high in 2020 and 2021 relative to what would be predicted based on the level of the refinancing incentive.

This evidence suggests that borrowers were using internet search very actively when shopping for mortgages in 2020-21, and if anything were searching more intensively during the pandemic than in prior refinancing booms.

[7] These last two outcomes are the only ones for which the COVID dummy is statistically significant at $p < 0.1$.

Figure A.16: **Changes in mortgage shopping behavior/preferences over 2019-20.** Each chart shows estimated calendar month coefficients and 95% confidence intervals (with March 2020 as omitted base category). Additional controls are included in each regression: loan amount category, FICO score, number of borrowers, indicators for purchase and cashout refinancing purpose, indicator for first-time homebuyers, indicators for loan program (GSE, FHA, jumbo, etc.), indicator for fixed-rate mortgage, LTV (and indicator for whether there is a junior lien), term, indicator for borrower race/ethnicity, education, age, gender, income, wealth components, risk aversion, and indicator for CRA low-to moderate income tract. Observations are weighted by the sample weights provided. Data source: NSMO.

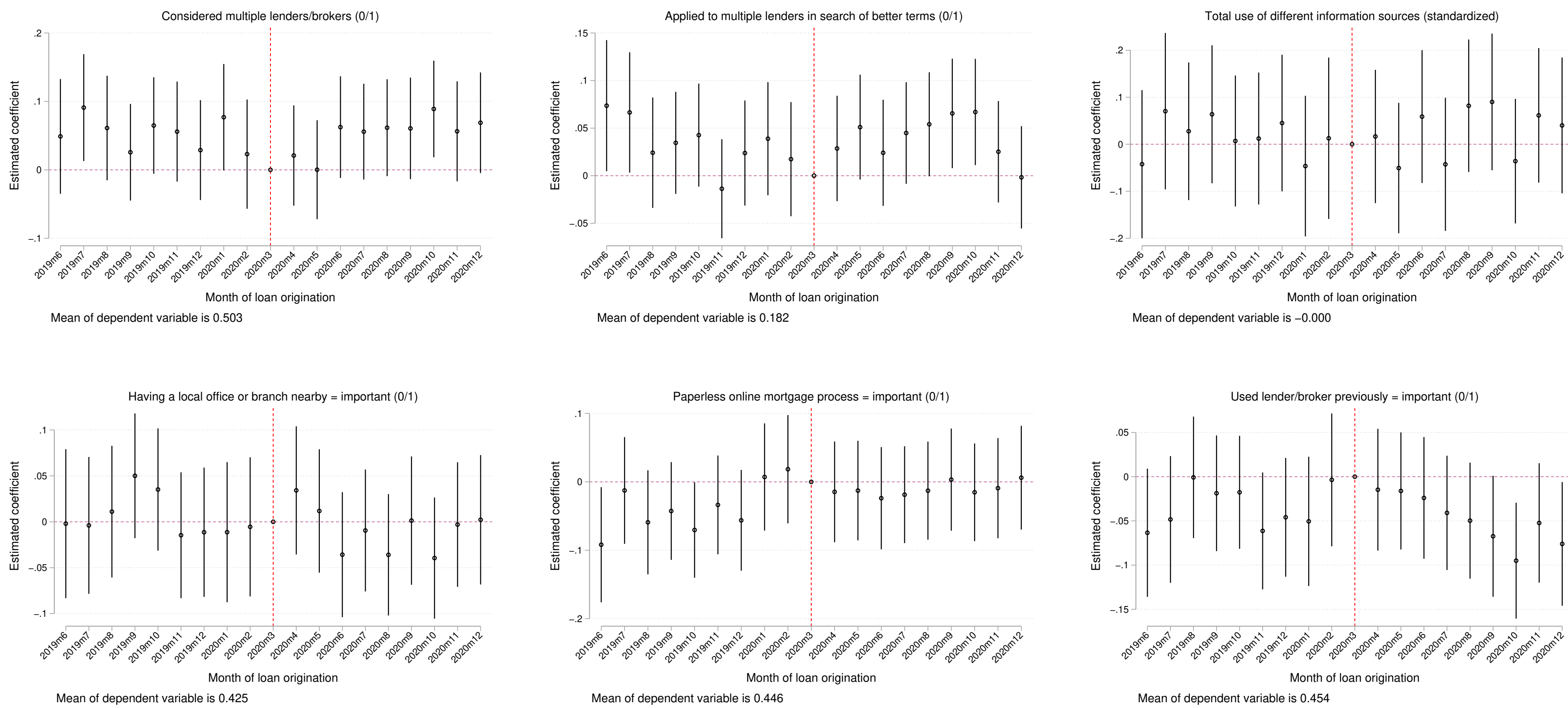
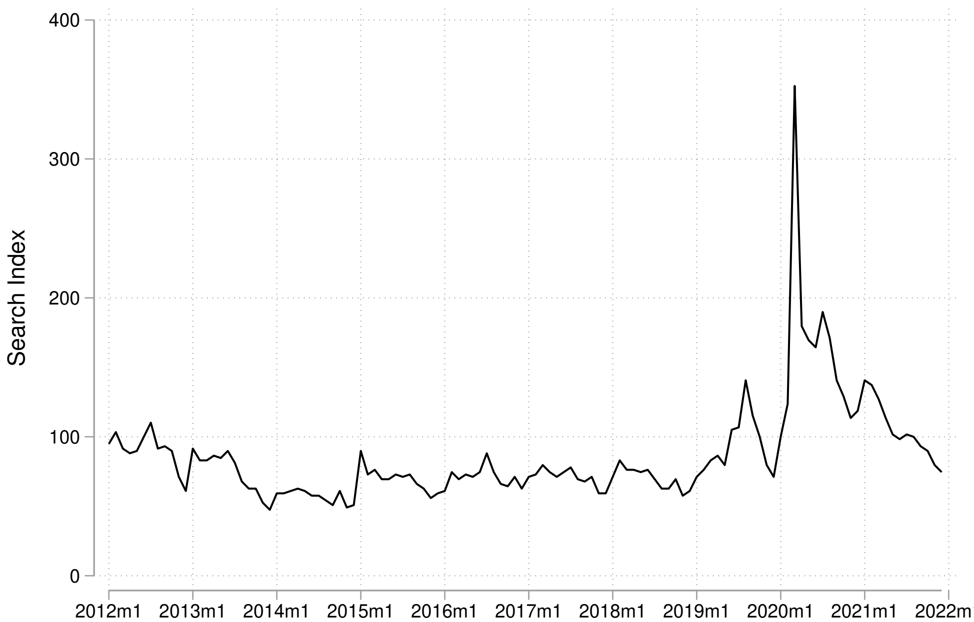
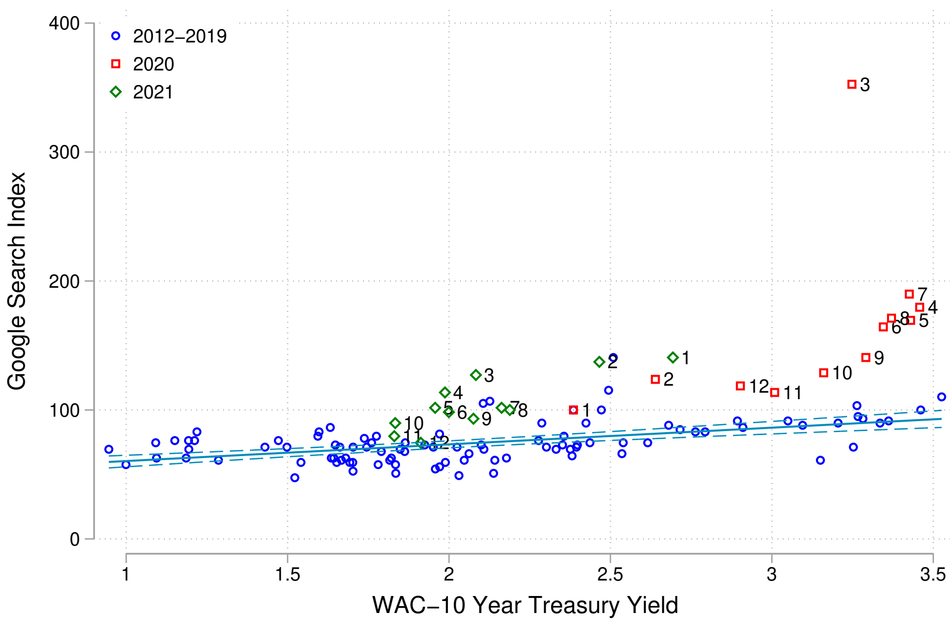


Figure A.17: **Web searches for mortgage refinancing.** The Google search index is constructed by averaging the searches for the following terms: mortgage rate, mortgage refinance, mortgage lender, refinance cost, mortgage cost. Data source: Google Trends.

A. Google Trends search index for refinance related terms



B. Google searches vs. the refinance incentive



F Additional Descriptive Statistics

F.1 Mortgage Non-payment by Credit Score Bin

Figure A.18 below presents a binscatter plot of the proportion of mortgages that were 60-plus days past due as of January 2020 and June 2020. The figure is based on McDash servicing data for mortgages originated since 2017. FHA loans are flagged based on the static loan type field in McDash. Figure A.19 shows the change in the past-due rate from January to June.

Non-payment rates increased across the credit score distribution for GSE, FHA, and portfolio loans. However, the rise in past-due rates was more pronounced for low-credit-score loans, consistent with the expectation that the pandemic has particularly amplified the credit risk for loans to less creditworthy borrowers. Note that a large share of these borrowers, although not all, took advantage of forbearance programs (e.g., Kim et al., 2024; An et al., 2021).

Figure A.18: **Non-payment vs. credit score: pre-pandemic vs. pandemic.** Data source: McDash data from ICE. Note: FHA loans are all classified as FHA, regardless of ownership. Conventional loans are categorized as GSE or portfolio based on the ownership status of the loan at the time of the data snapshot. "All loans" includes FHA, GSE, and conventional loans in portfolio, as well as VA loans and conventional loans held in private-label securities.

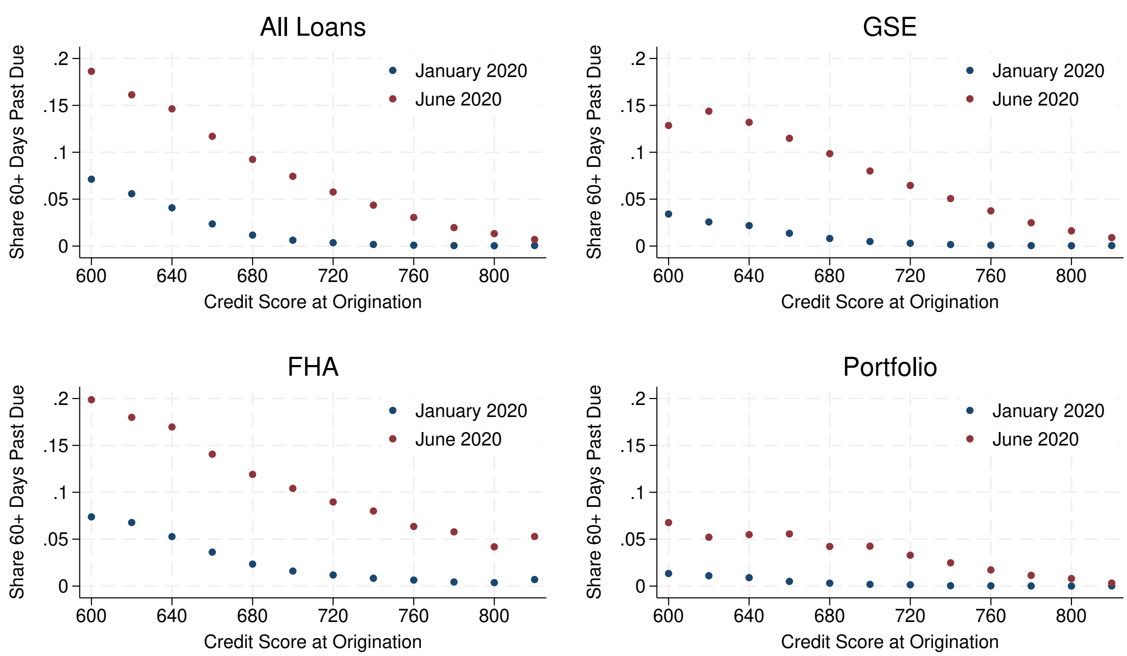
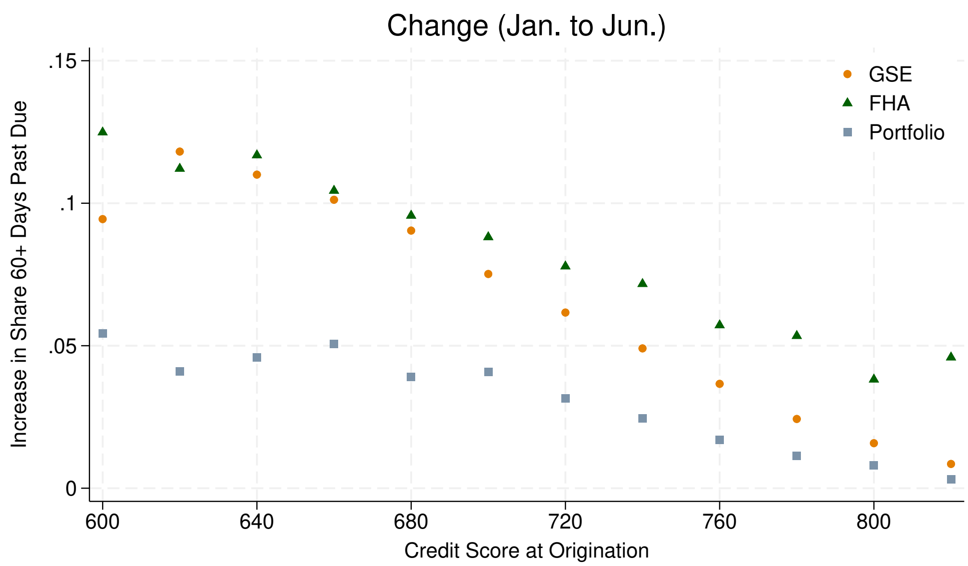


Figure A.19: **Non-payment vs. credit score: pre-pandemic vs. pandemic (percentage point change).** Data source: McDash data from ICE. FHA loans are all classified as FHA, regardless of ownership. Conventional loans are categorized as GSE or portfolio based on the ownership status of the loan at the time of the data snapshot.



F.2 Credit Score Distributions by Market Segment

Figure A.20: **Credit score distribution: conventional conforming loans.** Data source: confidential-use HMDA data. Includes originations of 30-year, fixed-rate conventional mortgages made to owner-occupants, weighted by loan balance at origination. Loans are grouped by application date weekly on Thursdays, including loans since the prior Friday. Dashed vertical line is March 2020.

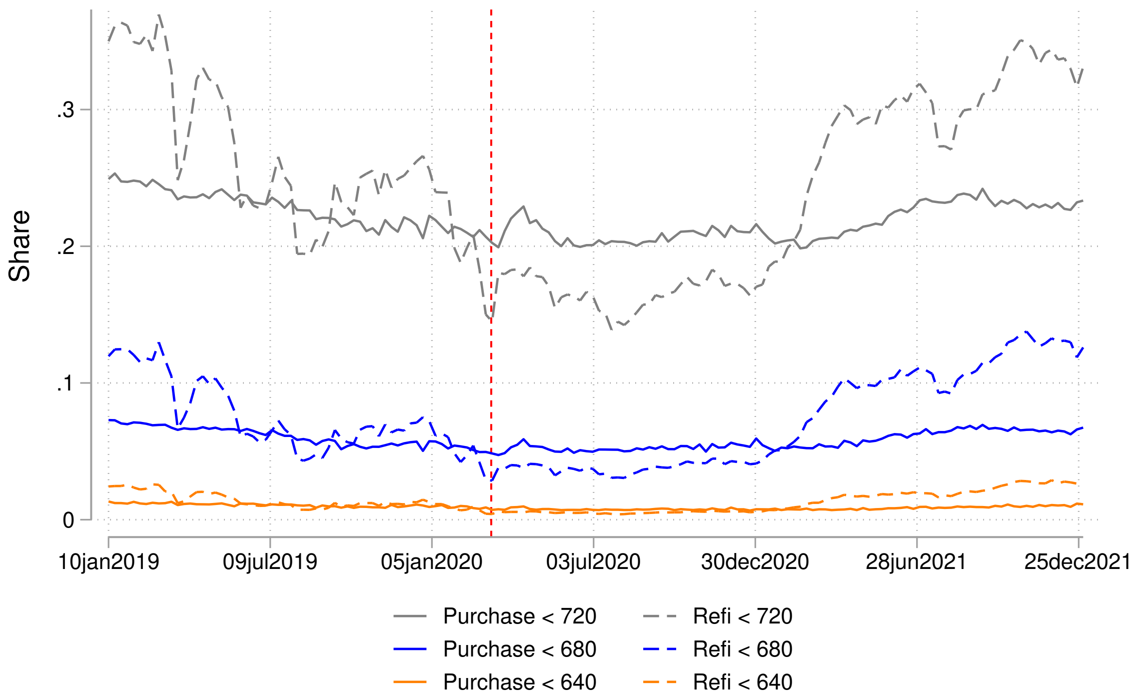


Figure A.21: **Credit score distribution: FHA loans.** Data source: confidential-use HMDA data. Includes originations of 30-year, fixed-rate FHA mortgages made to owner-occupants, weighted by loan balance at origination. Loans are grouped by application date weekly on Thursdays, including loans since the prior Friday. Dashed vertical line is March 2020.

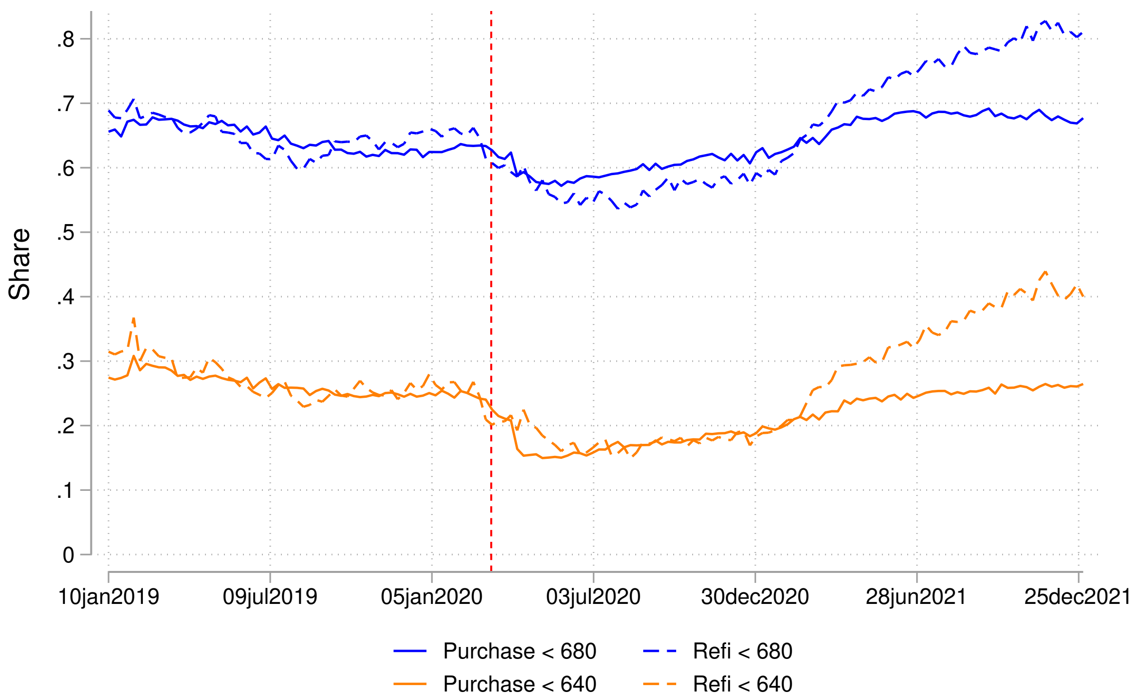
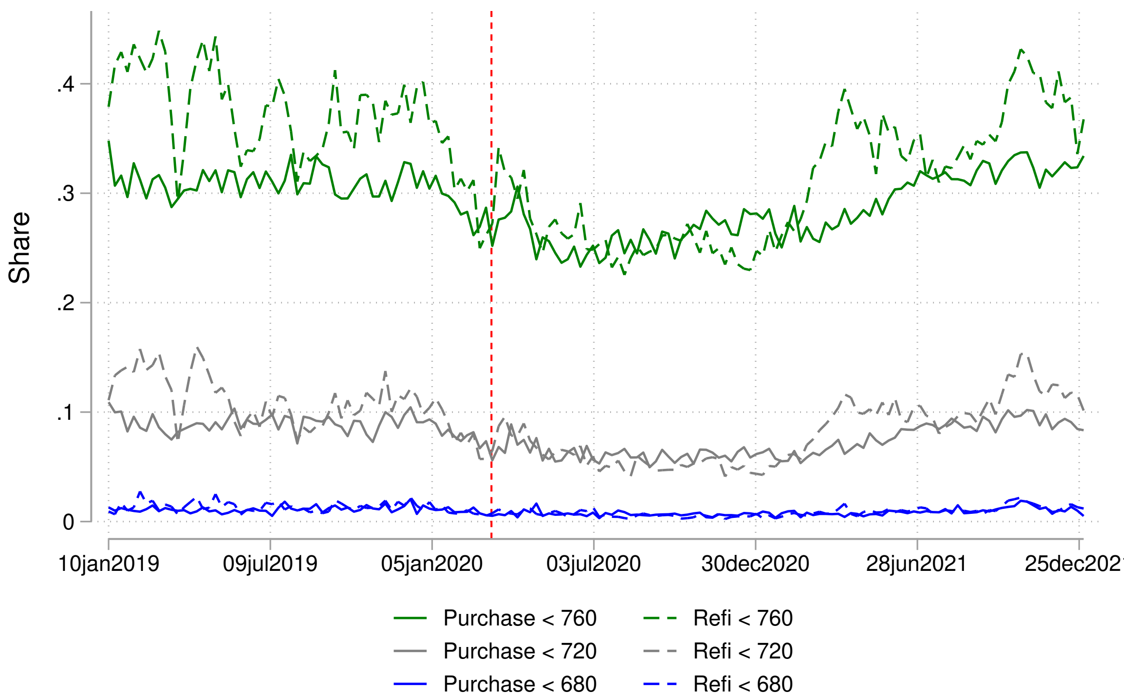


Figure A.22: **Credit score distribution: jumbo loans.** Data source: confidential-use HMDA data. Includes originations of 30-year, fixed-rate conventional mortgages made to owner-occupants, weighted by loan balance at origination. Loans are grouped by application date weekly on Thursdays, including loans since the prior Friday. Dashed vertical line is March 2020.



G Analysis of Credit Supply in Riskier Segments

This section analyzes credit supply in two riskier market segments, the jumbo market and the FHA market. The empirical results presented below underlie the discussion of credit supply in these two segments presented in Section VI of the main text. We also provide additional institutional details (e.g., discussion of the sources of risk facing intermediaries in these two segments).

G.1 The Jumbo Market

Jumbo mortgages are large loans exceeding the conforming limits for agency securitization. Jumbo borrowers typically have high incomes and credit scores, but jumbos are riskier for lenders and investors (usually banks) because they do not carry a government guarantee against credit risk. Comparing credit conditions in the jumbo and conforming markets therefore sheds light on whether these guarantees stabilized credit supply in the pandemic.

As part of our analysis, we also examine the supply of "superconforming" (or "conforming jumbo") loans. These are mortgages which exceed the national conforming loan limit but are still eligible for agency securitization because they are located in a county with a higher local limit.[8] Superconforming loans are still eligible for government guarantees, but for institutional reasons they are somewhat less liquid and are also less likely to be purchased by the Federal Reserve in its quantitative easing (QE) program. Studying the supply of superconforming loans after the resumption of Fed QE in March 2020 can shed light on how Fed MBS purchases affected mortgage credit supply, and in particular whether QE disproportionately boosted supply for the loans most likely to be purchased by the Fed.

G.1.1 Evidence from Optimal Blue

To begin, we use Optimal Blue data to estimate the interest rate spread on jumbo mortgages compared to smaller but otherwise identical conforming mortgages, following our earlier methodology. Results are presented in Figure A.23.

Panel A plots the jumbo-conforming offer rate spread for a prime mortgage with LTV of 80 and credit score of 750. Before the pandemic, this spread was fairly stable at 10-25bp. During the pandemic, however, it increases sharply to 80-100bp from April through August 2020, before partially normalizing to a level of about 50bp by the end of 2020.[9] The jumbo-conforming spread based on rate locks (Panel B) follows a similar pattern; the

[8] Fannie Mae and Freddie Mac cannot purchase or securitize mortgages exceeding the relevant conforming loan limit. The national conforming limit ($510,400 in 2020 for a single-family home) applies in most counties, but the limit is higher in counties with high home prices, up to $765,600 in 2020. A superconforming mortgage is a loan with a principal balance between the national limit and the relevant local limit. See Vickery and Wright (2013) for further institutional details.

[9] Optimal Blue data also indicate a large increase in the jumbo-conforming spread for 5/1 adjustable-rate mortgages.

spread rises from 0-10bp to a peak of 40-50bp from April through August, then declines to about 30bp by December. (Note: These rate lock estimates are based on the same regression model approach we used to study the conforming market in Section V.B.) We also see a similar rise and fall in the jumbo-conforming spread in time-series rate data from *Mortgage News Daily* and the Mortgage Bankers Association—see Figure A.24.

We also use rate lock data to track the evolution of the superconforming-conforming spread. These estimates are reported in Panel B of Figure A.23, based on the same methodology (i.e., we include a vector of superconforming dummy $\times$ time variables in our rate lock model, then plot the coefficients and confidence intervals). The superconforming spread does indeed rise early in the pandemic, from 10-20bp to 30-35bp, coincident with the resumption of Fed MBS QE in mid-March 2020, suggesting that QE had "local supply" effects in the conforming market where purchases were concentrated. This increase is less persistent than the rise in the jumbo-conforming spread, however. See Section G.1.3 for further discussion.

Turning to quantities, we observe a sharp contraction in the number of lenders offering jumbo mortgages during the pandemic, particularly for riskier borrowers (Panel C of Figure A.23). The number of lenders offering jumbo loans to prime borrowers with a credit score of 750 drops by more than half in the early stages of the pandemic, before slowly recovering to about 20% below pre-pandemic levels by December 2020. For lower FICO borrowers (680 and 640), the number of active lenders collapses—quite strikingly—almost to zero, and remains low through year-end. Finally, Panel D of Figure A.23 analyzes the share of rate locks that are for jumbo loans rather than conforming loans. This share declines by about half, both for purchase loans and refinances, before recovering.

Figure A.23: **Credit supply in the jumbo market.** Measures of credit supply computed using the methodology described in Section V.B. Vertical line represents the declaration of a national state of emergency on March 13, 2020. Data source: Optimal Blue.

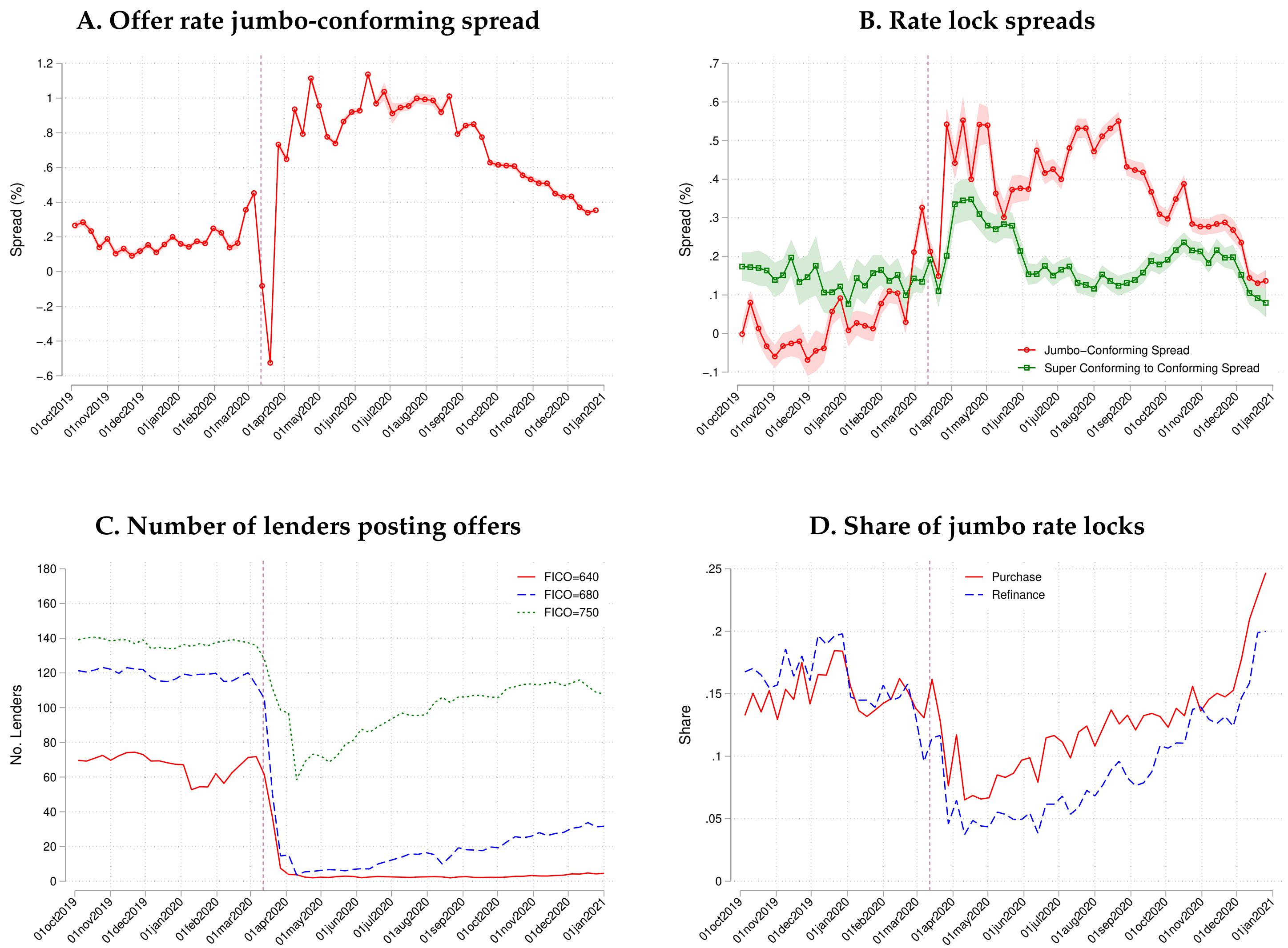
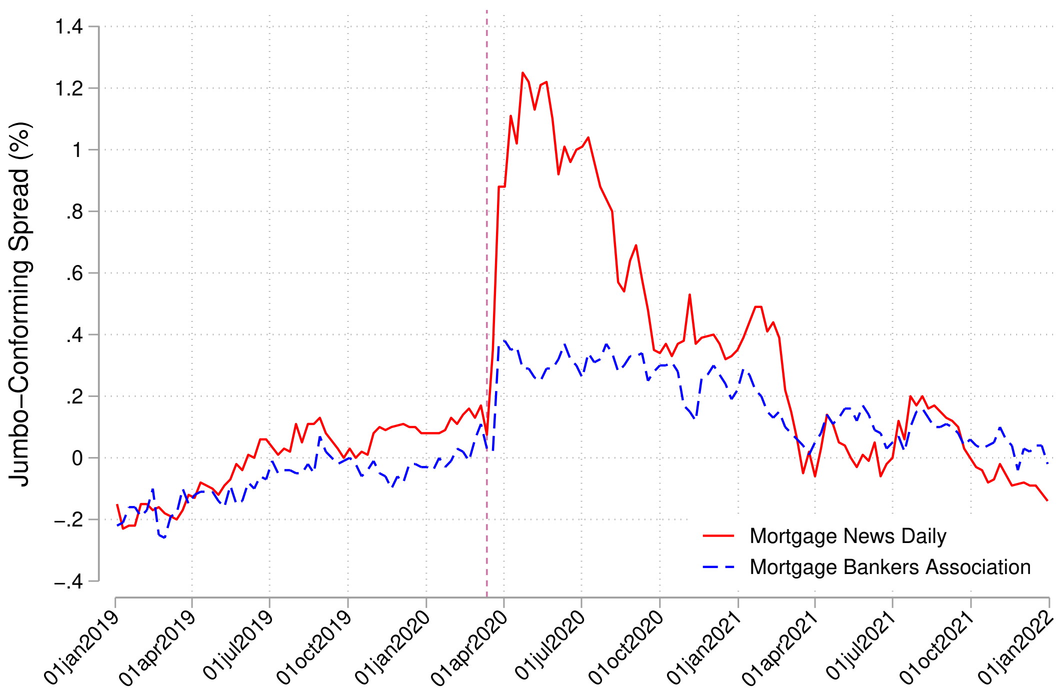


Figure A.24: **Jumbo-conforming spreads from other data sources.** Vertical line represents the declaration of a national state of emergency on March 13, 2020. Data sources: *Mortgage News Daily* and Mortgage Bankers Association (via Haver Analytics)



G.1.2 Evidence from HMDA

This evidence on rates and quantities indicates a significant negative supply response in the jumbo market, although an important caveat is that Optimal Blue primarily reflects mortgages originated by nonbanks. Banks retain a strong presence in the jumbo market, and several large banks stopped purchasing jumbos from nonbanks during the pandemic (Eisen, 2020). A potential concern, therefore, is that the drop in quantity we observe in Figure A.23 simply reflects substitution in lending from nonbanks to banks.

For a more representative picture of the jumbo market, we turn to loan-level confidential-use HMDA data, which have excellent coverage of both banks and non-banks. We estimate linear probability models where the dependent variable equals 100 for a jumbo loan and zero otherwise. The key explanatory variable is a pandemic dummy, defined as an application date in March 2020 or later. In some specifications we control for a comprehensive set of loan and borrower controls to soak up changes in the composition of lending. We focus on a narrow window of 10% around the applicable conforming loan limit (either the national limit, or the relevant higher local limit for mortgages in high-cost counties).

Regression results presented in Table A.4 show that there was indeed a significant decline in the fraction of jumbo loans, of about 7-9 percentage points. These results are fairly similar in magnitude across purchase mortgages and refinances and are also robust to whether or not we control for loan characteristics. (Note: the set of controls used is listed in the table notes.)

Table A.4: **Change in Jumbo Share during the Pandemic.** Linear probability model, estimated using loan-level confidential-use HMDA data. Sample includes loans within 10% either side of the conforming loan limit (CLL) applicable to each loan (either the national or county-level limit, whichever is applicable). Pandemic dummy = 1 if application date is March 2020 or later. Loan controls include: county dummies, debt-to-income (DTI), DTI^2, loan-to-value (LTV), LTV^2, credit score, credit score^2, log(appraisal amount), log(appraisal amount)^2, log(applicant income), log(applicant income)^2, applicant sex, applicant race and ethnicity, applicant age, an indicator for having no co-borrower, occupancy status, binned applicant age, and loan purpose (purchase, rate/term refinance, or cash-out refinance), where applicable. Sample period is July 2019 to December 2020. Robust standard errors in parentheses clustered at the county level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable = 100 if mortgage balance exceeds conforming limit

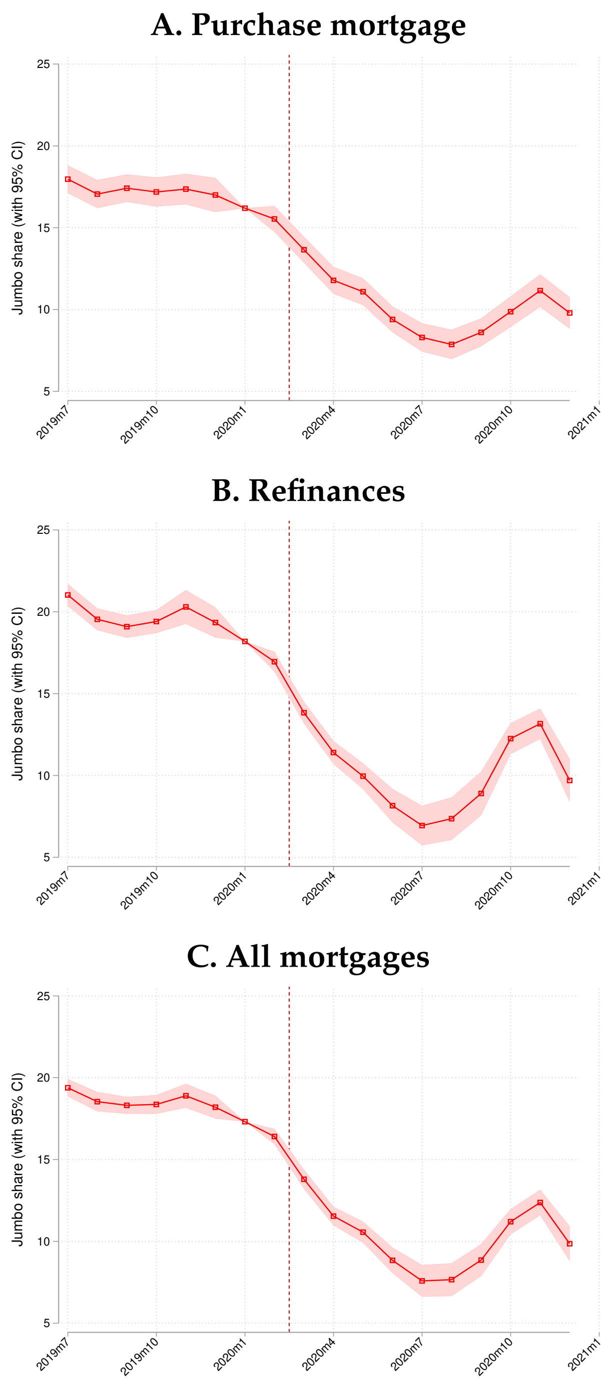
	(1)	(2)	(3)	(4)	(5)	(6)
Pandemic	-7.197***	-7.158***	-8.075***	-8.989***	-7.657***	-8.098***
	(0.215)	(0.217)	(0.390)	(0.408)	(0.289)	(0.312)
Num obs.	397,861	397,396	511,947	511,573	909,808	909,328
Mean of dep. var.	12.48	12.47	13.18	13.18	12.87	12.87
Origination type	Purchase	Purchase	Refinance	Refinance	All	All
Loan Controls	N	Y	N	Y	N	Y

To zoom in further, Figure A.25 traces out the dynamic evolution of the jumbo share over this period, by reestimating the model from Table A.4 replacing the pandemic dummy with a vector of application month dummies, then plotting the estimates and confidence intervals on these dummies. In 2019, shortly before the pandemic, jumbo loans make up about 20% of purchase volume and 17-18% of refinancing volume in the segment of the loan size distribution around the conforming limit. But the jumbo share declines sharply in 2020, reaching lows of about 8% for purchase loans and 7% for refinances by summer 2020, less than half of the pre-pandemic levels. We then see a partial recovery later in 2020, consistent with the decline in the jumbo rate spread documented earlier.

G.1.3 Disentangling Credit Guarantees vs. QE

An additional factor affecting the relative supply of jumbo and conforming loans in 2020 was the rapid expansion of Federal Reserve holdings of conforming mortgages through its agency MBS portfolio. The Fed purchased $580bn in agency MBS through the TBA

Figure A.25: **Evolution of jumbo lending share.** This figure displays estimated coefficients and associated 95% confidence intervals on a vector of time dummies from linear probability models where the dependent variable = 1 if the mortgage is a jumbo loan. The sample includes loans within 10% either side of the conforming loan limit. See notes from Table A.4 for a list of controls and other details. Models estimated using confidential-use HMDA data.



forward market in March and April 2020 alone (Frame et al., 2021), and its agency MBS holdings increased rapidly from \$1.37 trillion at the start of March 2020 to \$1.90 trillion by the end of June (source: Federal Reserve Bank of New York).[10] The pace of Fed TBA purchases slowed after April 2020, but the Fed continued to accumulate securities through 2020-21, with the portfolio peaking in size at \$2.7tr in early 2022.

This is important because research on quantitative easing (QE) shows that central bank asset purchases have "local" effects on the markets where purchases are directly concentrated (e.g., Krishnamurthy and Vissing-Jorgensen, 2011). Therefore, this rapid expansion in the Fed's portfolio would be expected to disproportionately affect credit supply in the conforming market *relative* to the jumbo market, where the Fed was not an active buyer.

Time-series evidence suggests QE did have a significant effect on credit conditions. First, Figure 2 in the main text shows that MBS yields declined sharply just after QE was announced, including a decline in OAS by about 40bp, and a fall in option cost due to a drop in interest rate volatility. (These changes were almost exactly offset by a rise in the primary-secondary spread, however, leaving the mortgage-Treasury spread little changed.) Second, the resumption of QE was associated with an increase in the jumbo-conforming spread in Figure A.23, indicating that asset purchases had disproportionate effects on the conforming market.

A limitation of these tests, however, is that the resumption of QE is closely tied to the financial and economic pressures at the time, which also likely amplified credit risk premia in the jumbo market. We therefore turn to the superconforming market as arguably a cleaner way to disentangle the supply effects of QE and credit guarantees.

Superconforming mortgages are useful for identification because they are guaranteed, but are significantly less likely to be purchased by the Fed. This is because the Fed obtains agency MBS pools through the "to-be-announced," or TBA, market, and pools comprising more than 10% of superconforming loans are not TBA eligible (Vickery and Wright, 2013; Huh and Kim, 2020). Matching eMBS loan-level data to security-level data on the Fed's MBS holdings, we confirm that the probability of an agency mortgage ending up in a pool in the Fed's MBS portfolio does indeed drop sharply just above the national conforming limit, declining by about 40%.

As we showed in Panel B of Figure A.23, the superconforming-conforming spread does indeed spike upwards just after the resumption of Fed MBS QE in mid-March, by about 20bp. The *jumbo*-conforming spread also rises, by a larger amount—about 35-40bp. This suggests that both QE and credit risk premia were important during this early phase of the pandemic (since the jumbo-conforming spread reflects both factors while the superconforming spread just reflects the former). The rise in the superconforming spread

[10]Note that there is some delay between the timing of the Fed purchases and the growth in the portfolio because the TBA forward trades settle only once per month. The Fed also executed a significant volume of dollar roll transactions during this period to delay settlement of its purchases. See Frame et al. (2021) for further discussion.

is less persistent though, lasting for only two months or so until the start of June. This matches the timing of Fed purchases—as we have discussed, the pace of forward asset purchases was much more rapid in March and April 2020 (reflecting settlements through May) than later in 2020.

Next, we use HMDA data to study effects on the quantity of credit. To separate the effects of QE from credit guarantees, we restrict the HMDA sample to mortgages in high-cost counties and we study shifts in lending in a 10% window around both the *national* conforming loan limit and the higher *local* limit. In the former case, the outcome variable is a dummy for whether the loan is a superconforming mortgage; in the latter, it is a dummy for whether the mortgage is a jumbo loan. In all specifications, we include a battery of loan controls to account for compositional shifts in lending (see table notes for a list of controls).

Table A.5: **Change in Jumbo and Superconforming Share, High-Cost Areas Only.** Linear probability model, estimated using loan-level HMDA data. Sample includes loans within 10% either side of the conforming loan limit (CLL). Sample is restricted to "high-cost" counties where the county-level CLL exceeds the national CLL. Pandemic dummy = 1 if application date is March 2020 or later. Loan controls include: county dummies, debt-to-income (DTI), DTI^2, loan-to-value (LTV), LTV^2, credit score, credit score^2, log(appraisal amount), log(appraisal amount)^2, log(applicant income), log(applicant income)^2, applicant sex, applicant race and ethnicity, applicant age, an indicator for having no co-borrower, occupancy status, binned applicant age, and loan purpose (purchase, rate/term refinance, or cash-out refinance), where applicable. Sample period is July 2019 to December 2020. Robust standard errors in parentheses clustered at the county level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable = 100 if mortgage is above national or local conforming loan limit

	$>$ national CLL			$>$ local CLL		
	(1)	(2)	(3)	(4)	(5)	(6)
Pandemic	-4.965***	-7.322***	-6.839***	-8.611***	-11.42***	-10.27***
	(0.351)	(0.266)	(0.255)	(0.302)	(0.594)	(0.462)
Num obs.	201,296	550,549	751,852	131,652	210,040	341,702
Mean of dep. var.	33.78	26.54	28.48	16.64	17.46	17.14
Mean Y [Pre-Pandemic]	36.66	29.56	31.87	22.25	24.23	23.43
Origination type	Purchase	Refinance	All	Purchase	Refinance	All
Loan Controls	Y	Y	Y	Y	Y	Y

Results are reported in Table A.5. In columns 1-3, the outcome variable is equal to 100 for a superconforming mortgage. Focusing on column 3, the share of superconforming loans in this part of the loan size distribution drops by 7pp after the pandemic begins, compared to a sample mean of 28%. Around the higher local limit, the share of jumbo mortgages drops by 10 percentage points compared to a sample mean of 17%. Therefore, the results indicate that both QE and guarantees promoted credit supply, although the effects around the local limit (the upper bound to qualify for government guarantees) are quantitatively larger, suggesting that credit guarantees had a relatively larger effect in bolstering credit supply.

We then explore the dynamics of these effects by replacing the pandemic dummy with a vector of time dummies (again, indexed by application date) and plotting them in Figure A.26 as event study plots. These estimates show that loan volume effects around the national limit (which reflect only QE) are significant in the early stages of the pandemic, but they are less persistent than the effects at the local limit (above which loans do not qualify for government guarantees). This timing is consistent with our earlier interest rate estimates in Figure A.23, which show that the superconforming-conforming spread is elevated only through June 2020, while the jumbo-conforming spread remains high throughout 2020.

G.1.4 Jumbo Analysis: Summary

We find a persistent increase in interest rate spreads and a decline in quantities in 2020 for jumbo mortgages that do not qualify for government credit guarantees. Analyzing the superconforming market, we estimate that these effects are in part due to Fed QE purchases of agency MBS backed by conforming loans, particularly in the spring of 2020. We interpret the remainder of the effect as being due to an amplification of the benefits of government guarantees due to the uncertain economic environment.

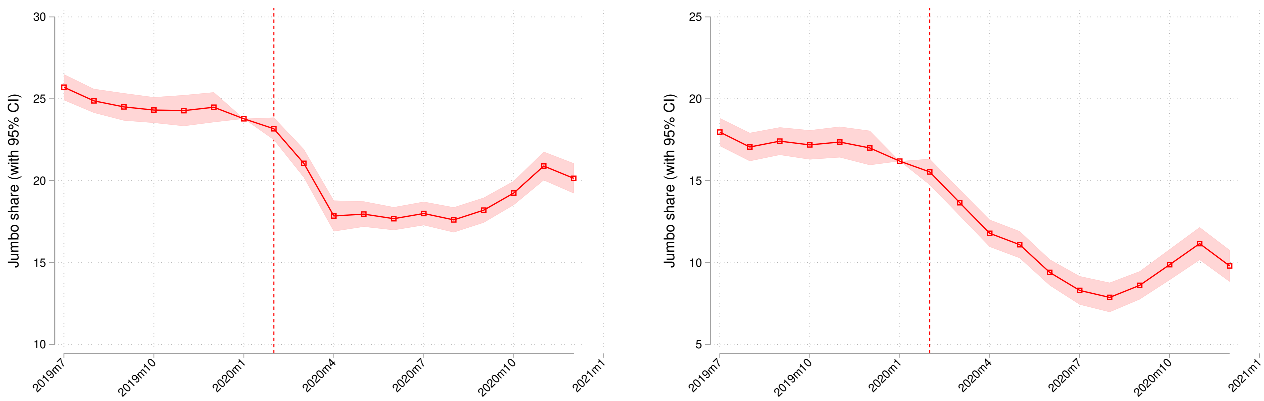
An alternative explanation is that our results reflect an amplification of the *liquidity* benefits of conforming mortgages, given that conforming loans can be easily sold into a liquid secondary market while jumbos are typically held on balance sheet by banks. This "liquidity" channel seems less plausible, however, given that banks had ample liquidity in 2020 (Li et al., 2020) and at the time were rapidly expanding their holdings of mortgage-related assets. The "credit risk" explanation is also consistent with the fact that jumbo credit supply declined more rapidly for less creditworthy loans.

Finally we note that, while we find that the effects of MBS QE faded after a few months, our estimates do not reflect the full general-equilibrium effects of QE. For example, the effects of QE on credit supply may have become more diffuse over time as investors had time to adjust the composition of their portfolios.

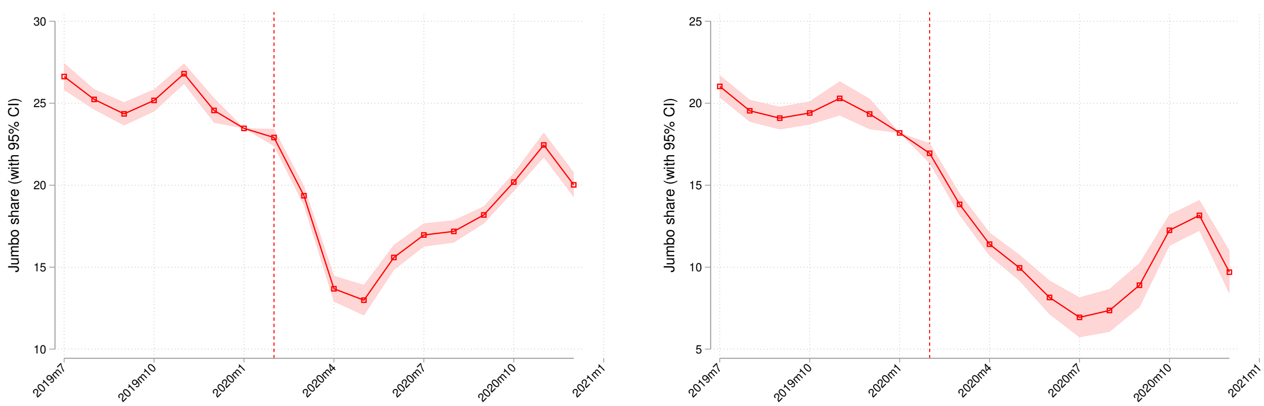
Figure A.26: **Lending above national vs. local conforming limit.** This figure displays estimated coefficients and associated 95% confidence intervals on a vector of time dummies from linear probability models where the dependent variable = 1 if the mortgage is larger than either the national or local conforming limit. The sample includes loans within 10% either side of the relevant conforming loan limit. See notes from Table A.5 for a list of controls and other details.

A. National conforming limit **B. Local limit**

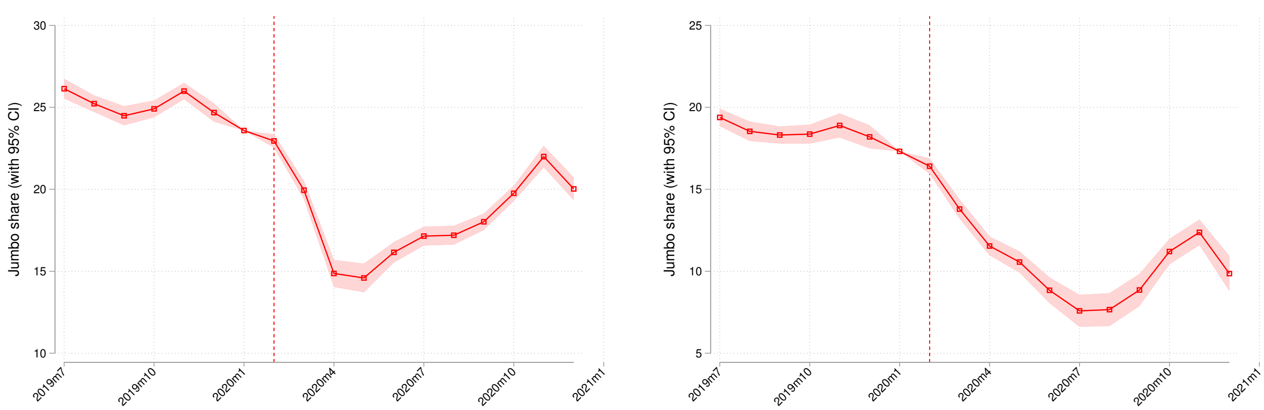
Purchase mortgages:



Refinances:



All loans:



G.2 The FHA Market

The FHA market is an important segment of the mortgage market that disproportionately serves lower-income borrowers and first-time homebuyers. While FHA loans are securitized and carry a government credit guarantee, these loans present more risk for mortgage intermediaries than a prime conforming loan due to institutional factors (Kim et al., 2018). First, intermediaries face liquidity risk because when an FHA borrower defaults, servicers are typically obligated to advance payments to investors until termination or modification (compared to four months in the conforming market), and they face significant delays before being reimbursed. This additional liquidity risk is likely to be particularly important for the nonbanks that now dominate FHA lending and servicing. Second, the servicer is not generally reimbursed for all the costs associated with foreclosure, and also faces some risk that the claim will be denied entirely. Tozer (2019) estimates that uncompensated costs average about $10,000 per FHA claim. Third, the likelihood of default is significantly higher because FHA borrowers are typically lower-income and often first-time home buyers.[11]

These factors are important because default risk was amplified during the pandemic, in part due to the creation of forbearance programs that allowed borrowers to pause their payments (see Section V.B for further discussion). It seems plausible that this heightened risk had a chilling effect on credit supply in the FHA market, despite the presence of government guarantees.[12] We test this "risk premium" hypothesis in two ways: i) by studying interest rates and quantities *within* the FHA market, comparing loans with different levels of default risk, and ii) by comparing credit conditions in the FHA market to the conventional conforming market.

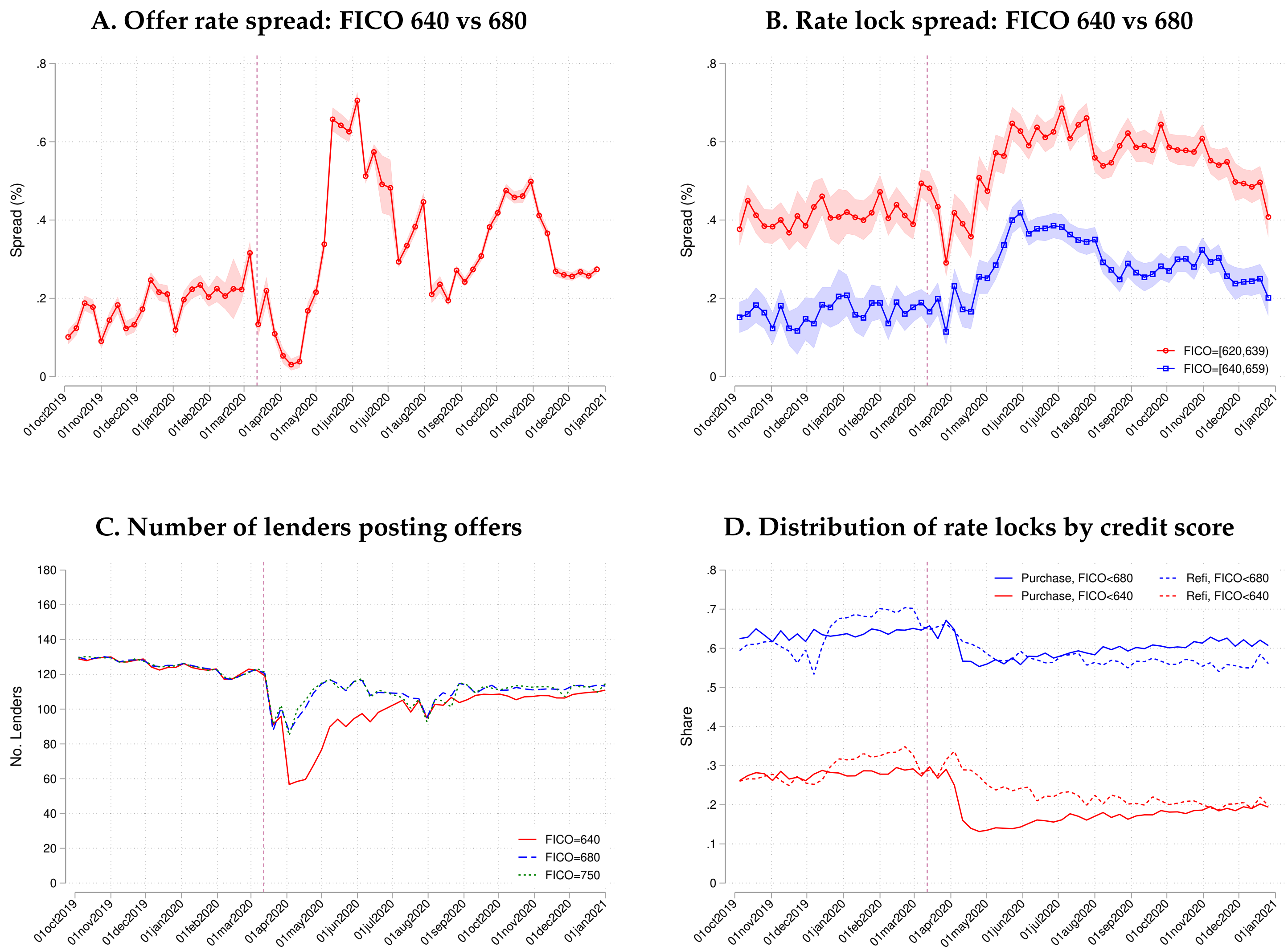
G.2.1 Default Risk and Credit Supply Within the FHA Market

First, we use Optimal Blue data to examine rates and quantities for FHA borrowers with higher versus lower default risk (based on credit score), using the methodology described in Section V.B. Results are presented in Figure A.27.

[11] In June 2020, 15.7% of FHA loans were 60 or more days past due, compared with only 6.7% of conventional loans. (Source: 2020:Q2 MBA delinquency survey.)

[12] Policymakers eventually took steps to limit the risks facing FHA lenders, in particular: (1) to limit liquidity outflows, the FHA determined that loans that re-perform after exiting forbearance can be made current by issuing a partial claim, reimbursing the servicer for principal and interest advances during forbearance; (2) Ginnie Mae created a temporary liquidity facility for servicers, the Pass-Through Assistance Program, or "PTAP."

Figure A.27: **Credit supply in the FHA market.** Measures of credit supply computed using the methodology described in Section V.B. Vertical line represents the declaration of a national state of emergency on March 13, 2020. Data source: Optimal Blue.



Panels A and B analyze interest rates on mortgage offers and rate locks, comparing borrowers with a FICO credit score of 640 versus 680.[13] The results show a clear increase in the interest-rate premium for the riskiest FHA borrowers. Panel A finds that in the mortgage offer data, the FICO 640-680 interest rate spread was stable around 20bp before the pandemic but rose sharply beginning in April 2020, coincident with the post-CARES Act surge in forbearance, peaking at about 70bp in June (50bp above pre-pandemic levels). The spread then decreased and displayed some volatility, but it remained elevated through the end of 2020. The low-FICO spread also increased in the locks data (Panel B of Figure A.27), although the peak increase was only about 25bp, half as large as in the offer data.[14]

Panels C and D of Figure A.27 study quantities, which also indicate a decline in credit supply to the highest-risk FHA borrowers. Panel C shows that the number of lenders offering any type of FHA loan drops by one-quarter during the market volatility in March 2020. In the highest-risk segment (FICO 640), the number of lenders then falls further in April, to half the pre-pandemic level. In contrast, lenders re-enter the market for lower-risk loans (FICO of 680 or 750) over the sample period. Lenders gradually return to the FICO 640 segment later in 2020. Similarly, Panel D shows that the share of FHA purchase rate locks to borrowers with a FICO score lower than 640 drops from 30% pre-pandemic to less than 15% in April, coincident with the spike in rate spreads and drop in the number of lenders.[15] Notably, we do not see such a sharp decline for FHA refinances. For an FHA issuer, refinancing an existing customer does not present additional risk, because the issuer is already responsible for advancing payments if the borrower defaults.[16]

G.2.2 Interest Rate Spreads: FHA vs Conforming Market

So far we have focused on variation in risk *within* the FHA market. Next we compare the cost of credit in the FHA market to the less-risky conforming market, estimating whether intermediation markups increased more quickly in the FHA segment, as measured either by the primary-secondary spread (Panel A of Figure A.28) or the gain-on-sale (Panel B

[13] A credit score of 680 is typical for FHA loans (roughly at the 60th percentile in the first quarter of 2020), while 640 is roughly at the 20th percentile; see Figure A.21 which displays the credit score distribution of FHA originations over the 2019–2020 period. (Figure A.20 and Figure A.22 plot credit score distributions for the conventional conforming and jumbo markets, for comparison). Other assumptions we apply for the offer data are that we study 30-year purchase-money FRMs with zero points, LTV = 95 to 97% (which is by far the most common in the FHA segment), and DTI of 36%.

[14] This difference between offers and equilibrium outcomes may reflect heterogeneity in supply responses across lenders—e.g., a subset of risk-averse lenders post very high rates for low-FICO loans, but these lenders comprise only a small share of locks because their uncompetitive rates mean that few borrowers choose them. We see a similar pattern in the jumbo results in Section G.1.

[15] As the figure shows, the fraction of loans to lower-than-680 FICO borrowers also falls but by a smaller amount. We also find similar patterns for quantities using originations from Home Mortgage Disclosure Act data—see Figure A.21.

[16] In fact, refinancing may even reduce risk by lowering the borrower's monthly payment (Fuster and Willen, 2017). Furthermore, a large majority of FHA refinances occur under a streamlined refinancing program that waives many requirements, including the need to conduct a property appraisal.

of Figure A.28). We measure these objects using the same methodology as our analysis of the conforming market in Section III, combining secondary market prices for Ginnie Mae securities from J.P. Morgan with primary market mortgage rates from the Mortgage Bankers Association.

While there is some volatility, in both cases we do indeed find a significantly larger increase in markups in the FHA market. For example, the gap in the primary-secondary spread between the FHA and conforming markets is close to zero pre-pandemic, but then increases to as high as 50-60bp. This is on top of the already large rise in the conforming spread that we document in the main text—put differently, the primary-secondary spread increased by roughly 100bp in the conforming market during the pandemic, but by up to 150bp or so in the FHA market.

The dislocation in markups between the FHA and conforming market is concentrated in 2020 and early 2021. By 2021:Q2 the gap in markups between FHA and conforming loans returned to levels similar to or even lower than pre-pandemic.

G.2.3 Risk vs Crowding-Out

The results seen so far are consistent with the hypothesis that the pandemic amplified the risk premium associated with FHA lending, which was then priced in the primary mortgage market. However, an alternative or complementary explanation is that FHA lending was "crowded out" due to lender capacity constraints. (See Sharpe and Sherlund, 2016 for evidence from prior periods that less creditworthy borrowers are crowded out during periods of peak demand.) This could occur if FHA loans are relatively more labor-intensive to underwrite or require more detailed interaction with the borrower.

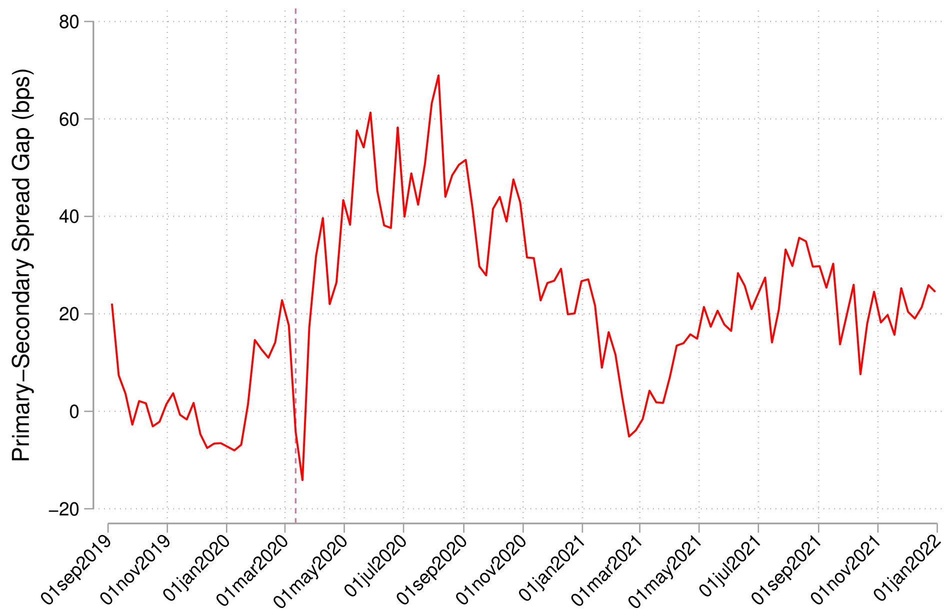
Disentangling these two explanations is challenging because both would predict a relative decline in credit supply to riskier borrowers. However, Table A.6 is able to make some progress by studying processing times as a proxy for the amount of effort involved in underwriting.

First, Panel A of Table A.6 tests whether FHA mortgages are more complex to underwrite by comparing the processing time of FHA and conforming mortgages over the period from July 2019 to December 2020. We do so with and without detailed loan controls and county fixed effects, but importantly always include lender-by-month fixed effects, so we study processing time differences *within* a lender at a point in time. The results suggest that FHA mortgages indeed take a longer time to originate: prior to the pandemic, purchase mortgages took about 3-4% longer in the FHA segment than in the conforming segment, while for refinances the difference was larger, at 13-14%. The interaction term with the "pandemic" dummy indicates that the difference further increased for purchase mortgages from March 2020 onward, although the same is not true for refinances.

These patterns suggest that it is indeed possible that FHA mortgages became relatively more expensive during the pandemic because lenders wanted to allocate their scarce resources towards mortgages that were easier to process. However, Panel B of Ta-

Figure A.28: **Comparing intermediation markups in the FHA and conforming markets.** Primary-secondary spread (Panel A) and gain-on-sale (Panel B) measured based on the methodologies described in Sections III.A.1 and III.C, respectively. Vertical line represents the declaration of a national state of emergency on March 13, 2020. Data sources: J.P. Morgan Markets and MBA (via Haver Analytics).

A. Primary-secondary spread: FHA minus conforming



B. Gain-on-sale: FHA minus conforming

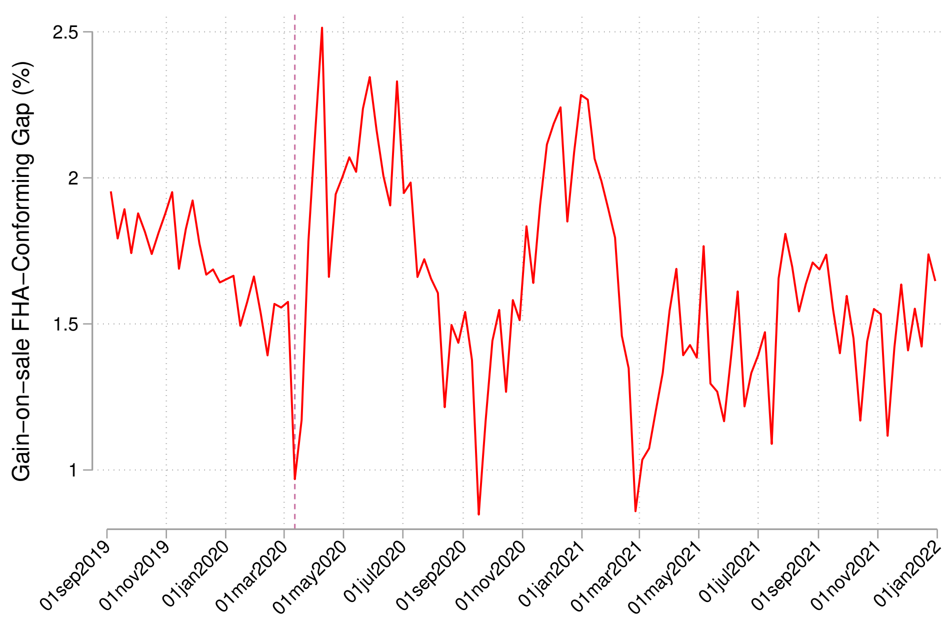


Table A.6: **Processing Times for More Complex Mortgages During the Pandemic.** Regression of mortgage processing time (measured as the difference between application date and action date) on two measures of loan complexity/risk: an FHA dummy and a dummy for credit score < 680. Estimated using loan-level HMDA data. Sample for Panel A includes FHA loans and conventional conforming loans, while sample for Panel B includes conventional conforming loans only. All specifications include lender $\times$ month fixed effects. Pandemic is defined as the period from March 2020 onwards, where the relevant time is the month of application. Loan controls in even-numbered columns include: a pre-application dummy, county dummies, debt-to-income (DTI), DTI^2, loan-to-value (LTV), LTV^2, credit score, credit score^2, log(appraisal amount), log(appraisal amount)^2, log(applicant income), log(applicant income)^2, applicant sex, applicant race and ethnicity, applicant age, an indicator for having no co-borrower, occupancy status, binned applicant age, and loan purpose (purchase, rate/term refinance, or cash-out refinance), where applicable. Sample period is July 2019 to December 2020. Robust standard errors in parentheses clustered at the lender level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

A. FHA Mortgages (vs. Conventional Conforming)

	log(processing time)				processing time (days, winsorized)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FHA	0.041***	0.029***	0.128***	0.144***	0.621	0.703***	5.636***	5.959***
	(0.007)	(0.004)	(0.039)	(0.031)	(0.440)	(0.227)	(1.349)	(1.134)
FHA $\times$ pandemic	0.015***	0.018***	-0.049	-0.023	1.272***	1.368***	-0.905	0.308
	(0.003)	(0.004)	(0.044)	(0.032)	(0.215)	(0.226)	(2.357)	(1.770)
N	5,315,040	5,313,561	9,568,310	9,566,126	5,315,040	5,313,561	9,568,310	9,566,126
Mean Y	3.73	3.73	3.90	3.90	49.95	49.95	56.83	56.83
Origination type	Purchase	Purchase	Refi	Refi	Purchase	Purchase	Refi	Refi
Loan Controls	N	Y	N	Y	N	Y	N	Y
County FE	N	Y	N	Y	N	Y	N	Y
Lender $\times$ month FE	Y	Y	Y	Y	Y	Y	Y	Y

B. Low-Credit-Score Mortgages in the Conventional Conforming Segment

	log(processing time)				processing time (days, winsorized)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FICO < 680	0.021***		0.111***		0.599*		5.924***	
	(0.005)		(0.007)		(0.326)		(0.231)	
FICO $< 680 \times$ pandemic	0.001	0.013***	0.004	0.019***	-0.036	0.808***	1.589***	2.123***
	(0.004)	(0.003)	(0.003)	(0.003)	(0.225)	(0.191)	(0.272)	(0.229)
N	4,181,063	4,179,846	8,828,705	8,826,559	4,181,063	4,179,846	8,828,705	8,826,559
Mean Y	3.73	3.73	3.90	3.90	50.10	50.09	56.93	56.93
Origination type	Purchase	Purchase	Refi	Refi	Purchase	Purchase	Refi	Refi
Loan Controls	N	Y	N	Y	N	Y	N	Y
County FE	N	Y	N	Y	N	Y	N	Y
Lender $\times$ month FE	Y	Y	Y	Y	Y	Y	Y	Y

ble A.6 finds that low-FICO conforming mortgages *also* take longer to process (compared to higher-FICO conforming mortgages), particularly during the pandemic, even though we previously showed that interest rates for such low-FICO loans did *not* differentially increase during the pandemic (Figure 9 in the main text).[17]

This evidence from the conforming market casts doubt on the idea that lenders actively used rate spreads across loan types to shift the mix of applications towards simple-to-underwrite loans. This conclusion is also in line with the findings of Frazier and Goodstein (2023), who study HMDA data and find little evidence that capacity-constrained lenders control demand by raising prices on loans to marginal borrowers.[18]

G.2.4 FHA Analysis: Summary

We find a more pronounced contraction in credit supply in the FHA market than the conforming market during the pandemic, reflected in a larger spike in mortgage interest rate spreads and gain-on-sale, as well as a decline in the volume of lending to the riskiest FHA borrowers and the number of lenders serving that segment.

While our results suggest that FHA credit supply contracted because of the higher risk in that segment, an alternative possibility is that lenders increased FHA markups because they instead wanted to focus on easier-to-originate conforming loans. This explanation is not fully consistent with patterns in the conforming segment though—high-risk conforming loans also seem more complex-to-underwrite but did not carry an interest rate premium during the pandemic. We view this as suggestive, although not decisive, evidence that high FHA markups in 2020-21 are at least partially due to risk.

In any case, under either interpretation, a key takeaway from our findings is that "government guarantees are not enough." We observe significant differences in credit supply between FHA loans and conventional conforming loans during the pandemic episode, even though both types of loans carry a government-backed credit guarantee.

[17] Based on columns (1) and (3), we see that without controls other than lender-by-month fixed effects, low-FICO loans take about 2% (purchase loans) or 11% (refinances) longer to refinance. Columns (2) and (4) indicate that, with all loan-level controls, processing times for low-FICO loans increased 1-2% during the pandemic (while the uninteracted low-FICO coefficient is no longer separately identified).

[18] Instead, Frazier and Goodstein (2023) present evidence suggesting that when capacity constraints are binding, lenders may ration supply to marginal borrowers before the application stage, perhaps by "not returning the calls" of such borrowers.