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 evolution of mortgage credit supply during the COVID-19 pandemic. We estimate that intermediation markups in the mortgage market increased sharply in 2020, evidenced by a sustained 100bp rise in the gap between mortgage primary rates and secondary market yields as well as higher gains-on-sale earned by lenders. Markups typically rise during periods of peak demand, but this historical relationship accounts for only part of the large increase during the pandemic. We present evidence that pandemic-related operational frictions and bottlenecks help explain why mortgage supply has been unusually inelastic, and also show that technology-based lenders have gained market share. In the cross-section, interest rate spreads have increased for loans posing the greatest credit risk to lenders. We conclude that, although the mortgage market experienced a historic boom in 2020, intermediation frictions magnified by the pandemic limited the pass-through of lower interest rates to borrowers.

Keywords: mortgage, credit, financial intermediation, COVID-19.

*Fuster: Swiss National Bank and CEPR. Hizmo: Federal Reserve Board. Lambie-Hanson and Vickery: Federal Reserve Bank of Philadelphia. Willen: Federal Reserve Bank of Boston. We thank Eric Hardy, Natalie Newton and Dick Oosthuizen for outstanding research assistance, Scott Frame, Philipp Schnabl, and numerous other colleagues for comments, as well as workshop participants at the Journal of Finance and Fama-Miller Center Conference on the Financial Consequences of COVID-19, University of Zurich, Louisiana State University, the Philadelphia Fed, Penn State University, and Dartmouth (Tuck). Opinions expressed in this paper are those of the authors and do not represent the opinions of the Federal Reserve Banks of Boston or Philadelphia, the Federal Reserve Board, the Federal Reserve System, or the Swiss National Bank.


I Introduction

2020 was an extraordinary year for the US mortgage market. Lenders underwrote a record $4 trillion of new first-lien mortgages, far higher than in any year since 2003.\footnote{Between 2008 and 2019, annual mortgage originations never exceeded $2.4tr, and exceeded $2tr only three times. Lending volume was $3.7tr in 2003, which was the prior record. The 2003 lending boom is still significantly larger in real terms or scaled by the stock of outstanding mortgages, however. Statistics are from Inside Mortgage Finance and can be seen on p. 8 of Urban Institute (2021).}

On the price side, the Freddie Mac Primary Mortgage Market Survey (PMMS) rate on 30-year fixed-rate mortgages (FRMs) fell below 3 percent for the first time since the series began in 1970, reaching lows of around 2.7 percent. Rocket Companies, the largest US mortgage lender, recorded $9.4 billion in net income, up more than 900% from 2019.

All this good news would be something of a surprise to market participants in March of 2020. The emergence of COVID-19 appeared to presage bad times for the industry. With the spread of the virus, lockdowns and social distancing, how would lenders close loans? Who would buy houses? How would mortgage servicers deal with commitments to pay principal and interest to investors as well as taxes and insurance when Congress had told borrowers that they could postpone payment without penalty? Yet borrowers and lenders seemingly overcame all these challenges.

Underlying these positive outcomes, however, are signs that the mortgage market has not functioned entirely normally during the pandemic. In addition to historically high lending and historically low rates, we have seen historically high spreads between mortgage rates and commonly used benchmarks. Figure 1 shows that while mortgage and Treasury rates generally co-move closely, the difference between the 30-year FRM rate and 10-year Treasury yield widened significantly during the pandemic, peaking at levels not seen since the 2008 financial crisis.\footnote{The effective duration of a 30-year mortgage is usually much closer to 10 years than to 30 years, because of prepayment. Although widely used, a 10-year Treasury note is not a perfect benchmark however, for reasons we return to below.}

And while mortgage lenders were highly profitable, industry practitioners reported tighter credit standards in response to the heightened risk of forbearance and delinquency.\footnote{For example, the Mortgage Bankers Association finds that mortgage credit availability dropped sharply at the onset of the pandemic, to its lowest level since the first quarter of 2014, and did not recover much through the end of 2020 (Mortgage Bankers Association, 2021).}

In this paper, we study the evolution of the mortgage market during the COVID-19

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pandemic, and evaluate the extent to which the events of the pandemic led to a contraction in mortgage credit supply. Our empirical analysis combines financial market data on MBS prices and yields, time-series data on mortgage interest rates, detailed microdata on mortgage rate offers and interest rate locks from the Optimal Blue platform, and several other mortgage datasets. We make four main points:

1. Except for a period of financial market turbulence in March, the high mortgage-Treasury spread is more than accounted for by a sustained 100bp increase in the “primary-secondary” spread—that is, by an increase in the price of intermediation in the primary mortgage market. A similar spike in the intermediation markup is observed based on measures of gain-on-sale earned by mortgage lenders. Thus, the situation is quite different to 2008, when mortgage rates were elevated due to the high spread on mortgage-backed securities (MBS) in financial markets.

2. Intermediation markups typically rise during refinancing booms, due to capacity constraints (Fuster et al., 2017). But this historical relationship accounts for only part of the increase in markups in 2020. In other words, the elasticity of mortgage supply was abnormally low. We present evidence that operational issues and labor market frictions related to the pandemic have contributed to this lower elasticity. Consistent with these frictions, we show that technology-based (“fintech”) lenders
gained market share for the types of mortgages which are more complex and labor-intensive to originate.

3. The mortgage rate spread increased for loans bearing the greatest credit risk for mortgage intermediaries. These span the socio-economic spectrum, including both non-guaranteed jumbo mortgages to high-income borrowers, and low-credit-score Federal Housing Administration (FHA) mortgages. The number of lenders offering credit in these segments of the market also fell sharply. In other words, although we find forbearance and default risk was not an important driver of the rise in intermediation markups for a standard prime mortgage, it led to a contraction of supply in some other parts of the market.

4. MBS purchases by the Federal Reserve (generally referred to as “quantitative easing” or QE) lowered mortgage rates and supported mortgage credit supply. We identify these effects in part using institutional features of the “to-be-announced” MBS forward market.

We are also able to rule out several plausible alternative explanations for the sharp rise in mortgage markups. Using geographic variation we show that factors related to local market competition, or the direct macroeconomic and health effects of the virus, did not play an important role; instead the rise in markups was broadly based. Using the cross-section of mortgages we show that forbearance and default risk did not play a significant role in the higher spreads observed in the prime conforming market, where lenders are less exposed to default than in other market segments. Finally, we show that borrowers shopped more and switched more frequently between lenders during the pandemic; along with our evidence on local competition, this speaks against the hypothesis that the high markups reflected an increase in lender pricing power.

Beyond helping to understand the behavior of the US mortgage market during the pandemic, our results yield more general lessons about the robustness and stability of the US mortgage finance system and the financial frictions that limit the pass-through of interest rate movements to borrowers. A first lesson is that, despite recent improvements in information technology, industry capacity constraints still bind during periods of peak demand. Although mortgage rates fell to record lows in 2020, our results imply that

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4 FHA mortgages are government-guaranteed, but these guarantees do not fully insulate mortgage intermediaries against default risk. See Kim et al. (2018) and the discussion in Section VI for more details.
rates paid by borrowers would be lower still under a system where rates adjust automatically with market yields during an economic downturn, for example under the automatic stabilizer mortgage proposed by Eberly and Krishnamurthy (2014) (see also Guren et al., 2020; Campbell et al., 2020), or under a system featuring a larger role for adjustable-rate mortgages. That said, we also find evidence that the market share of fintech lenders grew rapidly during the pandemic, either unconditionally or conditional on loan and borrower characteristics—suggesting that technology indeed helps to ameliorate capacity constraints and overcome operational bottlenecks (Fuster et al., 2019).\(^5\)

A second lesson is that government guarantees, which play a key role in the agency mortgage market, supported financial intermediation and lowered rates in the face of an event that amplified borrower credit risk, as was also the case during the Great Recession (Calem et al., 2013; Vickery and Wright, 2013). However, our results also highlight the limits of these guarantees: since lenders are not fully indemnified against risk, especially in the FHA segment, the pandemic induced a decrease in supply and increase in mortgage rates for the riskiest borrowers. Finally, we are able to disentangle effects of Fed QE (e.g., Di Maggio et al., 2020) and government credit guarantees by comparing rates on conforming, jumbo and super-conforming loans (which carry a government guarantee but are only partly eligible for Fed purchases). Both forces have promoted credit supply in the conforming segment, though in relative terms, the government guarantees appear to have had a more persistent effect on credit supply.

The evidence in this paper adds to a large body of research about the transmission of monetary policy and interest rate shocks through the mortgage market and the role of supply constraints, including Berger et al. (2020), Di Maggio et al. (2017), Fuster et al. (2013), and Fuster et al. (2017); see Amromin et al. (2020) for a recent review. Our results are also closely related to literature on the growing role of nonbank intermediaries in the mortgage market; nonbank lenders mortgage companies now originate more than half of new loans and are more sensitive to the liquidity risk associated with mortgage forbearance and nonperformance (Kim et al., 2018; Jiang et al., 2020; Buchak et al., 2018).

Finally, our results contribute to a growing body of research about the mortgage mar-

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\(^5\)Erel and Liebersohn (2020) show that nonbank fintech lending also gained importance in small business lending during the pandemic, accounting for a substantial portion of Paycheck Protection Program (PPP) loans. Kwan et al. (2021) show that banks with stronger information technology (IT) capabilities at the onset of the pandemic originated more PPP loans, and attracted more deposits during the pandemic.
ket and consumer credit markets more generally during the COVID pandemic. Cherry et al. (2021), Capponi et al. (2021), McManus and Yannopoulos (2021), and An et al. (2021) study mortgage forbearance during the pandemic. Agarwal et al. (2021) show that savings from refinancing during this episode were more skewed toward higher-income borrowers than in earlier refinancing waves. Other work on consumer credit markets includes Iverson et al. (2020) on bankruptcy and Horvath et al. (2020) on credit card borrowing, among others.⁶

II Data

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

II.A Optimal Blue

The Optimal Blue platform connects mortgage lenders to whole loan investors, allowing originators to search for pricing information, initiate rate locks and sell mortgages to investors.⁷ Lenders are typically nonbank mortgage companies, although smaller banks and credit unions are also represented. Investors are generally large banks and other institutions who retain loans purchased on the platform in portfolio or package them for securitization through Fannie Mae, Freddie Mac or Ginnie Mae. More than 1000 lenders and over 200 investors are active on the platform, and Optimal Blue estimates that the platform has been used to lock one-third of all mortgage originations in the US in recent years. It is plausible that this share further increased over the course of 2020, as nonbank originators gained additional market share in agency mortgage lending. According to Inside Mortgage Finance, among the top 50 lenders by volume in 2020, nonbanks accounted for 69.3% of loans originated in 2020, up from 60.0% in 2019. In 2020:Q4, nonbanks’ share was 74.4%.⁸

⁶Bracke et al. (2020) conduct a study similar in several respects to ours for the UK mortgage market, documenting a substantial tightening in credit standards and a drop in origination volumes after the onset of the pandemic. This again suggests that government guarantees in the US (which are absent in the UK) were important in sustaining mortgage originations.

⁷Optimal Blue data (as referenced throughout) is aggregated, anonymized mortgage market/rates data that does not contain lender or customer identities or complete rate sheets.

⁸Statistics reported in the 1/29/2021 issue of Inside Mortgage Finance. See also https://www.recursionco.com/blog/the-covid-19-nonbank-juggernaut-rolls-on, where it is shown that for mortgages securitized through Fannie Mae and Freddie Mac, the nonbank share increased
Our analysis makes use of two forms of information produced by the platform:

**Rate locks.** The first component is individual rate lock agreements for mortgages processed by Optimal Blue. These data include a comprehensive set of underwriting variables including the loan-to-value (LTV) ratio, FICO score, debt-to-income (DTI) ratio, loan amount, loan program, purpose (purchase or refinancing), asset and income documentation, employment and occupancy status, property type and ZIP code. The data also include unique identifiers for the lender, branch, and loan officer. The data cover a wide geographic area including about 280 metropolitan areas as well as rural areas.

Rate lock data have several advantages relative to the servicing data often used in mortgage research. First, the data include not only the mortgage note rate, but also the discount points or credits paid or received by the borrower, and the duration of the lock. This is important because in practice borrowers select from a menu of rate-point combinations, and average net points vary through time and across loan types. Second, we observe the exact date and time when the lock occurred, as opposed to the closing date which generally differs from the pricing-relevant lock date by weeks or even months. Third, the data are available in near real-time.

**Mortgage offers.** The second data source is information on the menu of mortgage contracts and associated interest rates offered by lenders through the platform’s pricing engine. Optimal Blue’s “Pricing Insight” allows users to retrieve the real-time distribution of offers (i.e. combinations of rates and net points and fees) for a loan with given characteristics in a particular local market. The interface is designed for lenders to compare their pricing against their peers. We use the Pricing Insight engine to undertake daily searches in one local market (Los Angeles), twice-weekly searches in four markets, and weekly searches for 15 additional markets, collecting information on offers for 100 different loan types representing different combinations of FICO score, LTV ratio, loan program, loan purpose (purchase or cash-out refinance), occupancy (owner-occupied or investor), rate type (30-year fixed or 5/1 adjustable), and loan amount by about 10 percentage points over July 2019-July 2020 in both the purchase and refinance segments.

A lock typically occurs at roughly the same time a borrower submits a loan application, although it can happen before or after.

All these searches condition on the mortgage requiring full income, asset and employment documentation, and that the mortgage finances a single-unit home. If a lender represents more than one investor, the offer we observe is based on the most competitive investor offer. For further detail, see Bhutta et al. (2021), who compare mortgage offer rates in the Insight data to interest rate locks to study the efficiency of borrower
Mortgage offer rates are an appealing object of analysis because they represent a direct measure of supply which can be observed regardless of whether the offer results in a loan in equilibrium. The Insight data also allow us to observe the evolution of the number of lenders active in different segments of the market since the onset of the pandemic. One limitation of the offer data, however, is that there is no fixed lender identifier, meaning that we are not able to track institutions over time or include lender fixed effects.

II.B Other Data Sources

We use a variety of other data sources. For mortgage rates, in addition to Optimal Blue, we use data from the Freddie Mac Primary Mortgage Market Survey and the Mortgage Bankers Association (MBA). All MBS pricing information comes from J.P. Morgan Markets. Mortgage servicing rights valuation data is provided to us by SitusAMC, an independent valuation service company. For direct evidence on lender income, we use the MBA Quarterly Performance Report. Data on mortgage industry employment comes from the Bureau of Labor Statistics’ (BLS) Current Employment Statistics, and job postings come from Burning Glass Technologies. Data on county-level daily COVID cases come from the NY Times GitHub repository. Evidence on borrower shopping activity is obtained from Google Trends. We also use public Home Mortgage Disclosure Act (HMDA) data for geographic market characteristics (e.g., lender concentration). Lastly, we use loan-level data from eMBS on mortgages securitized through Fannie Mae, Freddie Mac and Ginnie Mae to study the growth in fintech lending, as well as Black Knight McDash servicing data (“McDash data”) to measure overall market trends and to analyze the jumbo market.

III Mortgage Rates and Markups in the Conventional Conforming Market

In this section, we trace the evolution of mortgage rates and markups in 2020. We start, in Section III.A, by breaking down the spread between mortgage rates and benchmark 10-year Treasury yields, documented in Figure 1. In Section III.B, we use that decomposition to show that one component, the primary-secondary spread, a measure of intermediary search behavior in the mortgage market.
markups, largely explains the behavior of the mortgage-Treasury spread. In Section III.C, we calculate intermediary markups over the same period using gain-on-sale, an alternative and arguably more accurate measure. Gain-on-sale paints a very similar picture: both methods imply large increases in intermediary markups. In Section III.D, as a reality check, we confirm our asset price-based analysis by looking at intermediary income as reported by lenders, which also shows large increases.

Our focus in this section, and Section IV as well, is on the largest segment of the market, conventional conforming loans (which are generally securitized via Fannie Mae or Freddie Mac). These are typically “plain vanilla” 30-year fixed rate mortgages to prime borrowers making a down payment of 20% or more. As the core segment of the market, conforming mortgages rates and quantities are closely tracked by policymakers and market participants.

### III.A  Decomposing the Mortgage-Treasury Spread

Let \( r_p \) be the “primary mortgage rate,” the note rate paid by the borrower on a mortgage, and \( r_{10} \) be the yield on a 10-year Treasury note. Define \( r_s \) as the yield on a new-production MBS into which a typical newly originated mortgage with note rate \( r_p \) would be securitized and we can decompose the mortgage-ten year spread:

\[
 r_p - r_{10} = (r_p - r_s) + (r_s - r_{10})
\]

We can furthermore decompose the MBS yield spread as follows:

\[
 r_s - r_{10} \approx \left( r_{dur} - r_{10} \right) + \text{Option Cost} + \text{Option-Adjusted Spread (OAS)}
\]

*Duration adjustment* reflects the fact that the MBS may have a different duration from the 10-year Treasury. The duration of an MBS is not known *ex-ante*, since it depends on the prepayments of the homeowners in the underlying mortgages. These prepayments are estimated based on a model that simulates paths of future interest rates and prepayments under these paths; then, based on these simulations, the duration of the
MBS can be calculated. *Option Cost* measures the value of the prepayment option that is granted to the mortgage borrower, who can freely prepay their mortgage 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 that option, they require compensation for it in terms of a higher yield on the MBS. Finally, *Option-adjusted Spread* (OAS) is the residual spread that remains after the likely prepayments under the simulated interest rate paths have been accounted for. It can capture various additional factors that can affect the relative pricing dynamics in Treasury and MBS markets: for instance, liquidity differences, the risk absorption capacity of the marginal investors in the two markets relative to the supply of the securities, perceived credit risk differences, or non-interest-rate-driven prepayment risk (Boyarchenko, Fuster, and Lucca, 2019).11

### III.A.1 Measurement

While it is straightforward to obtain series for headline mortgage rates and Treasury yields, empirically decomposing the difference between these series into the four components shown in equations (1) and (2) is far less straightforward. Most importantly, MBS yields, durations, option costs, and OAS are not directly observed, but are obtained based on MBS pricing models featuring interest rate simulations and prepayment projections; we rely on models from J.P. Morgan Markets, as noted earlier. Further complications are that MBS are only traded in coupons of increments of 0.5 percent, and a mortgage with a given note rate could possibly be securitized into different newly produced coupons; additionally, MBS investors do not receive the entire note rate as some portion of the cash flow is diverted to pay for the agency credit guarantee (g-fees) and servicing. We account for this by calculating a net note rate:

$$\text{Net Note Rate} = r_p - g - s. \quad (3)$$

As our baseline measure of $r_p$, we take the 30-year FRM rate from the Freddie Mac PMMS; for the guarantee fee $g$ we take the effective g-fee on new production MBS from Fannie Mae’s 10Q disclosures; and the (base) servicing fee $s$ is set to 25 bps, which is the market

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11For textbook descriptions of MBS pricing, see e.g. Fabozzi (2016) or Davidson and Levin (2014). Note that the decomposition in (2) is not exact, since the OAS and the “zero-volatility spread” (which is 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 left-hand-side measure is a simple spread at a given point on that curve.
convention for GSE MBS. We then calculate the MBS yield, the MBS duration, option cost, and OAS based on interpolating between two MBS coupons surrounding the Net Note Rate.

### III.B What Happened Over 2020? How Does It Compare to 2007-09?

As shown in Figure 1, the gap between the conforming mortgage rate and the 10-year Treasury yield was around 1.8-1.9% at the beginning of 2020. It started rising in mid-February, rapidly increasing to a peak of about 2.75% in the last week of March. The gap subsequently gradually normalized, but even in June and July of 2020 still was at a steady level of about 2.4%, or 50 bp higher than at the beginning of the year. The mortgage-Treasury spread returned to pre-pandemic levels below 2% only after mid-October 2020. What accounts for these movements?

Panel A of Figure 2 shows the decomposition of the changes in the spread from the beginning of 2020 to end-November into the four components discussed above. We discuss them in turn, starting with the components of the MBS yield spread in equation (2):

- The duration adjustment became gradually more negative after February 2020, meaning that holding all else constant, MBS yields (and thus mortgage rates) should have fallen more than Treasury yields. This is because the model-implied duration of newly originated mortgages fell after the start of the pandemic: in January, a typical new mortgage pool had a duration of 4.7 years, whereas in July, it was only 3.2 years.

- The option cost slightly increased from late January through mid-March, along with a spike in market-implied measures of interest rate volatility.\(^\text{12}\) However, it then receded as fixed income markets normalized, and mostly remained at lower values than at the beginning of the year.

- OAS spiked in the first half of March, along with other dislocations in financial markets. This spike was the main cause of the initial opening of the gap between mortgage rates and Treasury yields. However, once the Fed announced that poten-

\(^{12}\)The close link between the option cost and interest rate volatility is intuitive: higher volatility in future interest rates makes it more likely that homeowners’ prepayment option will be in the money, thereby making the option more valuable.
tially unlimited MBS purchases would be conducted in order to ensure the smooth functioning of the market, OAS normalized, and over most of the year was lower than at the start of 2020.

In sum, while the MBS-Treasury yield spread did spike in the first half of March 2020, it then rapidly normalized and is not the reason for the high mortgage-Treasury spread from March-October 2020. Instead, a persistent rise in the primary-secondary spread is responsible.

For comparison, panel B of Figure 2 conducts the same decomposition of the mortgage-Treasury spread over the financial crisis period June 2007 - May 2009 when, as shown in Figure 1, the spread was similarly elevated. The figure illustrates that the sources of the rising spread are very different between the two episodes: during the financial crisis it is the spread on MBS in secondary financial markets that accounts for the unusually high gap between mortgage rates and the Treasury yield curve, at least until early 2009 when financial markets started to normalize.

III.C Measuring Intermediation Markups: Gain-on-sale

The primary-secondary spread examined above is appealing in the context of decomposing different factors affecting mortgage rates actually paid by borrowers. It is also frequently followed by policy makers and market commentators, thanks to its apparent simplicity. However, it has a number of conceptual shortcomings, as discussed in detail in Fuster et al. (2013) and Fuster, Lo, and Willen (2017).

Most importantly, the primary-secondary spread does not accurately capture how banks and nonbank mortgage lenders think about the margin they earn from originating a mortgage which is securitized in the MBS market. Rather than “earning” the mortgage rate and “paying” the MBS yield over the life of the loan, originators earn most of their margin upfront, as the difference between the amount they receive from selling the loan in the secondary market and the amount paid to the borrower. The only relevant “flow” income over the life of the loan is the servicing strip (equal to 25bp per year in case of GSE loans, and 44bp for FHA loans). This can either be earned by the mortgage originator, or by another firm that acquires the right (and obligation) to service the loan. The value of the mortgage servicing right (MSR) is usually capitalized and incorporated in the
calculation of the lender margin, which is often referred to as the “gain-on-sale.”

Formally, consider a mortgage with initial balance $S_0$. Assume that time is continuous and the loan has constant prepayment hazard $\lambda_p$. Using the notation from above, the value of the loan is

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

Assuming that the lender can sell the loan in the MBS market for $V$, the lender’s profit or “gain-on-sale” on the loan would then be $V - S_0$. If we assume that the prepayment hazard is constant and exponential, i.e. $S_t = S_0 e^{-(\lambda_p) t}$, then

$$\frac{V - S_0}{S_0} = \frac{r_p - r_s - g}{r_s + \lambda_p}$$  

Equation (4) still misses a few 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. In addition, servicers deduct the costs of servicing the loan, so the servicing income flow is $s(1 - c_s)$ where $c_s$ is the cost of servicing as share of servicing income. Second, the lender typically collects points and fees at origination, which we denote $F$, so the initial cash outlay is not $S_0$ but $S_0 - F$.\(^\text{13}\) Taking those two issues into account, we can write gain-on-sale as:

$$\pi_{\text{Gain-on-Sale}} = \frac{r_p - r_s - g - s}{r_s + \lambda_p} + \frac{s(1 - c_s)}{r_s + \lambda_p} + \frac{F}{S_0}$$  

\(^\text{13}\) $F$ is net of payments the lender needs to make to the securitizing GSE when selling the loan, called loan-level price adjustments (LLPAs).
Our empirical approach to measuring gain-on-sale follows Fuster, Lo, and Willen (2017). To compute the value of secondary market income, we assume that the lender sells the loan in the TBA market. Specifically, we start with $r_p - g - s$ and interpolate between the two nearest MBS coupons (for example, if $r_p - g - s = 3.25$, we take the equal-weighted average price of a 3.0 coupon and a 3.5 coupon security). For valuation of the MSR, we use valuation multiples provided to us by SitusAMC, an independent valuation service company. These multiples are based on transaction values of brokered bulk MSR deals, surveys of market participants, and a pricing model, and should capture the net value of servicing, i.e., the value of the income flow minus expected costs. The multiples are provided to us at monthly frequency at the coupon-by-loan type (GSE vs. FHA) level. All components are expressed per $100 loan amount, as is standard in the industry.

Figure 3 compares our estimates for intermediation markups based on the simple primary-secondary spread measure from Section III.A.1 and the gain-on-sale methodology from this section. Panel A shows the primary-secondary spread based on three different mortgage rate series, the PMMS survey rate (our baseline), the Mortgage Bankers Association (MBA) weekly application survey, and the Optimal Blue Insight data. Despite some differences across the three series, the primary-secondary spread increases significantly at the onset of the pandemic regardless of which mortgage rate is used.

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14“TBA” stands for “to be announced,” which is the MBS market segment where new agency mortgages are typically forward-sold. See Vickery and Wright (2013) for additional institutional details.

15Fuster et al. (2017) consider an alternative measure, denoted $\phi$ in their paper, which follows equation (4) rather than equation (5) and values all cash flows based on their value in the MBS market. One can think of this as the price of intermediation from the point of view of the borrower. Fuster et al. (2013) calculate a measure of $\pi$ 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 Internet Appendix A.1, we show that results using OPUC are qualitatively similar.

16Appendix Figure A.8 shows the evolution of these multiples for conventional conforming and FHA segments. It shows that multiples for given fixed coupons decreased over time, in line with the overall level of market interest rates. However, for the interpolated multiple at the typical coupon rate for new loans, there was only a modest decrease at the onset of the pandemic, which reverted over the course of 2020.

17The PMMS and MBA surveys both ask lenders for rates offered and discount rates offered. Since the discount points change each week, the published survey rates are not directly comparable week-to-week. To address this, we assume that the borrower pays constant discount points and use the point-rate trade-offs estimated in the Optimal Blue offer (Insight) data for 2017-2020 to adjust rates. For prior years when Optimal Blue data is not available, we estimate these trade-offs using MBS prices.

18Internet Appendix Figure A.1 shows that the patterns are also qualitatively similar when using the Current Coupon (CC) as an alternative measure for MBS yields. The CC yield is not as reliable in this time period, however, since every MBS coupon traded far above par in 2020; see Fuster et al. (2013) for related discussion.
Panel B of Figure 3 shows time series of our estimates of gain-on-sale in the conforming market, based on the same three mortgage rate series. In all cases, gain-on-sale jumps by about 250 bp between mid-February and early April 2020. Gain-on-sale then stays high over the rest of the year: based on the PMMS and MBA series, it is on average roughly 200 bp higher than in the second half of 2019; with the Insight series, the increase is around 175 bp. If we compare panels A and B of Figure 3, we see similar patterns, with the main difference being that the primary-secondary spread (panel A) reverts more to its pre-pandemic level at the end of 2020 than gain-on-sale (panel B).

Gain-on-sale provides an indication of just how profitable mortgage lending was in the last three quarters of 2020. Originations over the period averaged over a trillion dollars a quarter and multiplication of our quarterly gain-on-sale measures by origination volumes implies total industry gain-on-sale of about 162bn dollars, or 54bn a quarter. Had gain-on-sale remained at its pre-pandemic level of 2.5 percent, the industry would have earned only USD 82bn over the three quarters—i.e. half as much as it did.

### III.D Lender Profit Margins

Direct evidence on intermediaries’ self-reported loan production profits also indicates record-high margins. We obtain data from the Mortgage Bankers Association Quarterly Performance Report, which collects quarterly data from roughly 340 mortgage banks on revenues and expenses since 2008:Q3.\(^\text{19}\) Panel A of Figure 4 plots the time series of average total net production income (in bps of loan amount) reported by the firms in the sample—meaning the margin between loan production revenues and expenses. We note that mortgage banks do not necessarily capture the entire intermediation markup, as they often act as correspondent lenders for larger banks (“aggregators”) which then sell the loans in the secondary market and also capture part of the markup.

Income in Q2 through Q4 of 2020 is extraordinary compared to all other quarters in the data. Net production income is around 60 bps in 2020:Q1, already at the higher end of incomes over the previous few years, but it was more than three times as high, 203 bps, in Q3. Furthermore, this higher net margin was earned on loan production that was almost twice as high. In panel B, we multiply the net production income by the average

\(^{19}\)Note that the sample of reporting firms changes over time, and we only have access to aggregate series, not firm-level series. Also, these statistics are not specific to the conventional conforming segment; they combine all originations.
reported origination volume per firm, which was USD 1335mn in Q3 and 1472mn in Q4, versus 728mn in Q1. The resulting total net production income therefore skyrocketed from below USD 5mn in Q1 to an average of 21.4mn over the remaining quarters of 2020, with a peak of over 27mn in Q3.

These data support our conclusion that the price of intermediation in the mortgage market was historically high in 2020. They also show that our high measured gain-on-sale at least partly translated into historically high lender profit margins rather than being absorbed by expenses not accounted for in our gain-on-sale calculations.\(^{20}\) In the next two sections, we study the role of different economic factors in accounting for the elevated intermediation markups observed during the pandemic period.

### IV Capacity Constraints

We first examine whether industry capacity constraints can explain the high intermediation markups documented above. Individual loan officers and underwriters are limited in how quickly they can process mortgage applications, and lenders face significant adjustment costs in hiring and training new workers, particularly in the short run. Fuster et al. (2017) find evidence that these constraints lead to an increase in mortgage markups during periods of peak demand—in other words, given limited capacity, lenders “step on the brakes” by increasing the margins charged to borrowers.\(^{21}\)

#### IV.A Is 2020 Consistent With Historical Patterns?

Figure 5 studies whether the historical relationship between intermediation markups and capacity utilization can account for the high markups in 2020. The figure plots mortgage demand against the two measures of intermediation markups we have used already: the primary-secondary spread, and the gain-on-sale \((\pi)\). Our preferred proxy for demand is the difference between the weighted average coupon (WAC) on the stock of existing

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\(^{20}\)For instance, Fuster et al. (2013) discuss pipeline hedging costs, which are proportional to implied interest volatility. However, while this volatility spiked early in the crisis, it has since been at or below its level of January and February 2020.

\(^{21}\)Consistent with the presence of capacity constraints, Fuster et al. (2017) show that loan processing times are strongly positively correlated with mortgage application volumes. Sharpe and Sherlund (2016) also find evidence of capacity constraints, showing that refinancing waves induce substitution away from complex mortgages which are more labor-intensive to process and underwrite.
mortgages and the 10-year Treasury yield. This measure is highly correlated with applications for (refinance) loans, and is arguably exogenous to current mortgage supply shocks because it does not rely on current mortgage rates.\footnote{In contrast, using the difference 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. See \textit{Fuster et al.} (2017) for further discussion. We find that the WAC–10 Year Treasury spread is highly correlated with an estimate of the percentage of active mortgage borrowers who are refinance candidates, measured both in monthly levels ($\rho = 0.77$) and monthly changes ($\rho = 0.70$) for the period January 2008 to October 2020. See \textit{Lambie-Hanson} (2020) for how refinance candidates are computed in this calculation.} We also use the MBA mortgage applications index as an alternative direct measure of demand.

The figure shows that the price of intermediation during the pandemic significantly exceeds what would be predicted simply based on the level of demand. Red squares in Figure 5 are from 2020, with the number indicating the calendar month of the observation. Blue circles are from 2012-2019. There is a clear positive historical relationship between intermediation markups and mortgage demand. But from around April 2020 onwards, intermediation markups are well above the line of best fit, regardless of which demand measure or intermediation markup is used.

Table 1 quantifies the “excess” markup by regressing the primary-secondary spread or gain-on-sale on either of the mortgage demand proxies and time dummies corresponding to different phases of the pandemic. In all cases, the pandemic dummies indicate large, statistically significant excess markups from March 2020 onward. The historical relation between markups and demand can only account for about 20-40% of the rise in intermediation markups, depending on the specification.\footnote{On the high end of this range, the gain-on-sale model in column 4 (estimated through February 2020) would predict a maximum increase in gain-on-sale of 109bp, given that the MBA applications index increased from an average of 449 in January 2020 to a maximum of 1002 (a 553 unit difference). This compares to an actual increase in gain-on-sale of 279bp.} \footnote{The pandemic dummies from March-August are comparatively smaller for gain-on-sale than for the primary-secondary spread, considering 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.}

Column 1 shows that the primary-secondary spread is 77bp higher than expected in March-May, and 86bp higher in June-August (i.e., it increased an additional 9bp). By comparison, the one-standard-deviation residual from this regression excluding the COVID period is only 8.9bp (last row of table). Thus, in terms of the primary-secondary spread impact, one could consider the COVID period roughly a “9 sigma” event which persists...
for well over six months. Results are similar in column 2, although the regression fit is slightly weaker. The excess intermediation markup is also highly significant when we use gain-on-sale as the dependent variable (columns 3 and 4). Gain-on-sale is $1.05-$1.30 higher than expected over March-May, increasing to $1.40-$1.60 over June-August.25

IV.B Operational Constraints in Expanding Capacity

We now document several pieces of evidence suggesting that operational issues related to the pandemic made it more difficult for lenders to expand capacity in 2020. This provides a plausible explanation for why the mortgage supply curve was unusually inelastic relative to prior lending booms.

IV.B.1 Labor Market Frictions

Anecdotal evidence suggests the remote-work environment created significant challenges in hiring, training and onboarding new loan officers, processors and other mortgage employees. One leading industry participant told us that it has been difficult to train new employees and to monitor their work, and that as a result lenders prioritized hiring experienced professionals (generally from competitors) who were well-known and trusted, and did not require much training or supervision. Consistent with this message, an executive at large nonbank lender Mr Cooper explained their limited expansion in capacity 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). The diversion of staff and managerial attention to process the wave of forbearance applications appears to have been an additional drain on the effective labor supply, at least early in the pandemic (Berry and Kline, 2020).

25Our measure could overstate true gain-on-sale if the SitusAMC servicing multiples we use exceed those used by market participants for their internal pricing. The most likely reason for a decline in the multiple for new originations would be the increased risk of mortgage forbearance and borrower default, which increases risk for the servicer. However, as we will see in Section V.A, conforming mortgage rates for borrowers with high default risk—for whom the value of servicing rights should have fallen the most under such a hypothesis—have moved in line with rates for less risky borrowers, speaking 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 servicing rights during the pandemic, observed transactions may understate going-concern values if they mainly reflect forced sales at fire-sale prices. Finally, even if we set the servicing valuation multiple to zero—a very extreme assumption—this would only reduce gain-on-sale by about $1, and thus still not bring the observed gain-on-sale fully in line with historical patterns.
Disruptions to the licensing of mortgage loan officers also held back growth in labor supply. Nonbank loan officers must be licensed through the Nationwide Multistate Licensing System (NMLS), a process including background checks, fingerprinting, an examination, and ongoing education. During the early months of the pandemic, half of fingerprinting locations were shuttered, and around 10 percent remained closed as of December 2020. Testing sites also closed in the early months, although NMLS began offering a remote testing option in September. These factors limited the inflow of de novo loan officers, and also affected employees switching from banks to nonbanks or changing their state of employment.

This qualitative evidence suggests that the supply of labor was relatively inelastic during the pandemic, which would imply unusually slow hiring compared to the level of labor demand, and also a sharp increase in the price of labor. We now present evidence supporting these predictions.

Panel A of Figure 8 shows that lenders added nearly 50,000 mortgage loan officers and underwriters (MLOs) after the emergence of COVID in March 2020. This took MLO employment to a post-financial crisis high of 360,000, although employment remained 120,000 MLOs short of its all-time peak in 2004. Data from Burning Glass in Panel A also shows a sharp rise in MLO job postings during the COVID period. Postings fluctuated around 1 vacancy per 100 employees prior to COVID, but jumped to more than 2 per hundred during the pandemic.

To test whether MLO hiring was low relative to postings, we estimate the following

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26 A new license is required not just for de novo loan officers, but also for experienced loan officers transitioning from banks to nonbanks or moving across states. In the latter two cases, the loan officer is permitted to temporarily operate for 120 days before receiving a new license (Mortgage Bankers Association, 2019). We were told however that in some cases licensing delays exceeded this 120 day grace period.

27 In an email communication, one industry participant told us: “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.”

28 Burning Glass Technologies is an employment analytics and software company that crawls over 40,000 online job boards and company websites daily, scraping and cleaning information on job postings. We focus on job postings with the O*NET job code 13-2072, which includes professionals who evaluate, authorize, or recommend approval of commercial, real estate, or credit loans, including mortgage loan officers and agents, collection analysts, loan servicing officers, loan underwriters, and payday loan officers. We further capture “mortgage loan officers” as postings in this category that have the words “mortgage,” “mtg,” “home,” or “residential” in the job title.
\[
\log(MLO_{t+1}) - \log(MLO_t) = \alpha + \beta_1 p_t + \beta_2 p_{t-1} + \beta_2 p_{t-2} + \epsilon_t,
\]

where the dependent variable is the log change in MLO employment between mid-month \( t \) and mid-month \( t + 1 \) (from the BLS Current Employment Statistics, Establishment Survey) and \( p \) are monthly MLO postings per employee from Burning Glass. The regression is estimated on data from March 2012 to February 2020. Coefficients are shown in Internet Appendix Table A.1 and imply a correlation of about 0.5 between actual employment growth and employment growth predicted by using just current and lagged job postings.

Panel B of Figure 8 presents predictions from this regression model which illustrate how anomalous the pandemic period was for the hiring-vacancies relationship. Dots labeled “COVID” are out-of-sample predictions for March 2020 to December 2020. Actual employment growth fell short of the predicted value in all ten months. Overall, we estimate that monthly employment growth averaged about 1.5 percentage points less than we would expect. In Panel A, the line labeled “Counterfactual Employment” quantifies the cumulative effect of this hiring gap. Actual MLO employment at the end of 2020 was 60,000 lower than what would be predicted based on the historical relationship between postings and employment growth.

Turning to the cost of labor, it is difficult to observe the compensation packages offered to loan originators, which often involve a combination of signing bonuses, fixed salary, and loan volume incentives. Nevertheless, available data from the Mortgage Bankers Association, analyzed in Appendix B.2, is consistent with a significant increase in labor costs during the pandemic. Labor costs per dollar of loan volume typically fall significantly during lending booms, because of scale economies; but we show labor costs declined only slightly during the 2020 boom. A conservative estimate is that personnel expenses scaled by loan volume were unusually high by at least 25 bps by 2020:Q4, more than 10% of average personnel costs measured over the previous five years.

IV.B.2 Operational Issues in Mortgage Origination

The pandemic also made the process of originating a mortgage more complex and uncertain. Obtaining documentation of borrower employment and income was often challenging because many businesses were physically closed, and the high rate of job loss often
required rechecking employment status multiple times before closing (Berry and Kline, 2020). County recorder officers were closed or operating on limited schedules, making it hard to complete title searches and causing delays in recording the mortgage, which in turn raised concerns about the potential for fraud (Hughes, 2020). Other steps in the process, such as property appraisals and notarized signing of closing documents, were more cumbersome due to social distancing. E.g., Michael Fratantoni of the Mortgage Bankers Association noted that: “there are steps in the process that are still physical, like the actual mortgage note. If it’s a paper note, someone still has to show up at the office and collect those and send it on to the next step in the process.” (Berry and Kline, 2020)

IV.C Technology and Capacity Constraints

The mortgage industry has undergone significant technological change in recent years. Did technology play a role in expanding lending capacity and mitigating operational and labor market frictions during the pandemic? For instance, information technology can enable the origination process to be less labor-intensive and more automated, and thereby more scalable, consistent with Fuster et al.’s (2019) finding that technology-based mortgage lenders adjust processing capacity more elastically. Technology-based lenders are also likely to rely on digitized records rather than paper documents, and be able to transition their workforce more easily to remote work. It is also possible that borrowers placed more value on a high-quality online platform during the pandemic, given the challenges of face-to-face interactions and the transfer of physical documents.

We use loan-level data from eMBS and the classification of “fintech” lenders from Fuster et al. (2019) to assess whether technology-based lenders expanded lending more rapidly during the pandemic. We investigate two questions. First, did fintech lenders

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29 Rocket Mortgage CEO Jay Farner emphasized this scalability in the context of the 2020 refinancing wave in the firm’s 2020:Q3 earnings call, as reported by industry newsletter HousingWire: “Farner also said Rocket was able to scale more aggressively than competitors due to its tech stack and business model, which he said is far more efficient because it doesn’t require disproportionately high headcounts.”

30 E.g., Rocket Mortgage CEO Farner said during the company’s third quarter earnings call that “Demand for a completely digital experience has never been stronger and Rocket is delivering.” (Kleimann, 2020).

31 The Fuster et al. (2019) classification identifies six mortgage lenders which offered a fully online application process as of the end of 2016: Rocket (Quicken Loans); Better Mortgage; Guaranteed Rate; LoanDepot; Movement Mortgage; and Supreme Lending (Everett Financial). Online lending platforms are much more ubiquitous in 2020, but this set of lenders remains near the technology frontier today. Relying on this list also limits the influence of lookback biases or subjective judgements about which lenders are technology leaders today, because the Fuster et al. (2019) classification was set well before the start of the pandemic. It
increase their overall market share? Second, did they particularly gain market share for mortgages which are complex and time-intensive to underwrite? This second test is motivated by Sharpe and Sherlund (2016), who find that capacity constraints induce lenders to ration credit by prioritizing simpler and less labor-intensive mortgage applications. Following Sharpe and Sherlund, we use low-credit-score loans and purchase mortgages as measures of these more complex-to-underwrite loans.

We estimate linear probability models in which the dependent variable is a dummy equal to one if the originator is a fintech lender in the Fuster et al. (2019) classification. The right-hand-side variable of interest is a pandemic dummy equal to one for mortgage applications underwritten and processed during the pandemic, which given the time to close a loan we proxy by an origination date after March 2020. The model is estimated using loan-level eMBS data on agency mortgage originations, combining data from Fannie Mae, Freddie Mac and Ginnie Mae. The sample period is January 2019 to December 2020. Like Fuster et al. (2019), our main specifications exclude bank loans from the sample, to isolate differences between fintech lenders and other nonbank lenders with a similar funding model and common regulatory environment.

Results in Table 2 indicate a significant increase in the fintech market share during the pandemic, particularly for complex loans. Columns 1-3 focus on purchase mortgages, which are typically more complex and labor-intensive to underwrite than refinancings. In column 1, which includes no controls (i.e. a simple difference in means) the fintech share is 2.7 percentage points higher during the pandemic than in the previous year or so. Column 2 controls for state fixed effects (the most granular geographic information in these data) as well as loan and borrower characteristics such as quadratic functions of credit score, debt-to-income and loan-to-value (see table notes for full list of controls). The coefficient is slightly smaller, at 2.2 percentage points, but remains economically and statistically significant. Quantitatively, the increase is about one-quarter of the sample mean of 10.65. Column 3 includes a pandemic × (credit score < 680) interaction term, which indicates that the rise in fintech share is significantly larger for low-credit-score mortgages. The total effect for these loans is about 4.2 percentage points.

The next three columns focus on refinancings, the sector where fintech lenders historically specialize. Interestingly, the overall fintech share of refinancings is little-changed
during the pandemic, although again the fintech share does rise for low-credit-score borrowers, as shown by the positive interaction term in column 6. The final three columns are based on a pooled sample including both purchase mortgages and refinances. The increase in the fintech share estimated in these columns reflects both their gains in the purchase market as well as a compositional shift in mortgage lending towards refinancings.

In Internet Appendix C, we trace out the timing of these changes by replacing the pandemic dummy with monthly time dummies and plotting the resulting coefficients. The purchase-mortgage graph is particularly striking: the fintech market share is very stable at around 7 percent prior to the pandemic, but then jumps sharply by about three percentage points as the pandemic takes hold, before declining late in 2020 as conditions start to normalize. As an additional robustness test, we also re-estimate the analysis in Table 2 retaining bank lenders in the sample. The results (also presented in the Internet Appendix) are similar to our main estimates.

These results support the view that technology and automation helped the mortgage industry manage the capacity constraints and operational challenges associated with the pandemic. In particular, the fintech market share increased most markedly for purchase mortgages and loans to low-credit-score borrowers, exactly those loans which are typically rationed during periods of binding capacity constraints on mortgage underwriting resources (Sharpe and Sherlund, 2016).

V Alternative Explanations: Risk, Health and Competition

We now consider several other plausible explanations for the rise in the conforming mortgage intermediation markups, related to default and forbearance risk, the direct health and economic effects of the virus, and lender market power. The evidence we present below suggests that none of these factors play an important role in accounting for the high intermediation markups in 2020.

\footnote{We have also investigated the composition of the increase in the fintech share, finding that it is broadly based across the set of six firms classified as technology-based lenders.}
V.A  Forbearance & Default Risk

The pandemic led to a surge in mortgage forbearance and delinquency, reflecting high unemployment and a CARES Act provision requiring servicers to provide up to a year of forbearance on federally-backed mortgages.\(^{33}\) Heightened delinquency creates significant risk for mortgage lenders and servicers, even in the conforming market where loans are securitized and carry a credit guarantee. First, there is liquidity risk because the servicer is required to 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.\(^{34}\) Second, there is “pipeline” risk that the loan becomes delinquent just after origination, before it can be sold.\(^{35}\) Third, servicing a delinquent loan is much more labor-intensive and costly.

We use the cross-section of mortgage rates to study whether this heightened default risk led to a risk premium which increased intermediation markups during the pandemic. Our approach makes use of the fact that the rise in delinquency was much larger for low-credit-score borrowers (see Internet Appendix F for detailed evidence based on McDash servicing data). If rising default risk is being priced into conforming mortgage rates we should therefore see an increase in the interest rate spread between low- vs high-score conforming mortgages. We first estimate this interest rate spread using Optimal Blue Insight data on mortgage offers. Each observation in the Insight data is an interest rate offer for a given lender, location, number of points and combination of loan characteristics. Our data includes searches for otherwise identical mortgages with a FICO score of both 680 and 750. We measure the rate premium for with a FICO 680 loan by estimating the regression:

\(^{33}\)At the peak in June 2020, 8.6% of all mortgages were in forbearance (source: Mortgage Bankers Association). The total mortgage delinquency rate more than doubled during the early part of the pandemic: from 3.2% in January 2020 to 7.8% by May (Black Knight Financial Services, 2020).

\(^{34}\)This was a cause of great industry concern 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 (Federal Housing Finance Agency, 2020). This cap does not apply to taxes, insurance and other payments.

\(^{35}\)Such loans would typically 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). See https://www.hud.gov/sites/dfiles/OCHCO/documents/2020-16hsngml.pdf and https://bankingjournal.aba.com/2020/04/fhfa-to-purchase-qualified-loans-in-forbearance.
rate_{int} = \alpha_{mt} + \beta_t \times (FICO_i = 680) + \epsilon_{int}, \quad (6)

where rate_{int} 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 \alpha_{mt} are CBSA × week fixed effects. Other loan characteristics are held fixed (e.g., DTI=36, LTV=80 and balance of $300K). \beta_t then traces out the evolution of the FICO 680-750 interest rate spread.

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

rate_{ilmt} = \alpha_{mt} + \delta_{lt} + \beta_t \times FICO \text{ bin}_i + \Gamma X_{ilmt} + \epsilon_{ilmt}, \quad (7)

where rate_{ilmt} is the interest rate on lock i issued by lender l in CBSA m during week t; FICO bin_i is a set of five FICO bin dummies; \alpha_{mt} and \delta_{lt} are CBSA × week and lender × month fixed effects; and X_{ilmt} is a set of loan and borrower controls including log loan amount, DTI and DTI squared, and dummies for the 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 tradeoff measured each week in Optimal Blue Insight.\textsuperscript{36}

Estimates of \beta_t from these two models are reported in the top two panels of Figure 6. There is no evidence of a persistent increase in the interest-rate spread on low-FICO mortgages, either for mortgage offers or rate locks. The interest rate spread does spike temporarily in March, associated with the onset of the pandemic and dislocation in the MBS market. But by April, the interest rate spread returns to a narrow band around or even slightly below the pre-pandemic levels of about 40bp.

Data on quantities paints a similar picture. Panel C of Figure 6 plots the number of conforming lenders offering mortgages to borrowers with different FICO scores, calculated by averaging the number of nonmissing rate offers in the Optimal Blue Insight data across the 20 Case-Shiller metropolitan statistical areas (MSAs). The number of lenders drops

\textsuperscript{36}Borrowers pay discount points to buy down the interest rate on their mortgage. Conversely, mortgages with net credits have higher interest rates. The shape of the tradeoff between rates and net points moves over time, and has become flatter since the onset of the pandemic. Our Optimal Blue Insight data includes daily offered interest rates for loans with different numbers of net points (+2, +1, 0, -1 and -2). We use this pricing grid to adjust the interest rate on each loan to an equivalent zero-point loan. We then use this adjusted rate as our dependent variable. An alternative approach is to include additional controls interacting points and credits with time dummies; this generates similar results.
temporarily in March, and more so for lower FICO loans, but is subsequently quite stable and there is no evidence of significant rationing to low credit-score borrowers. Panel D plots the percentage of conforming rate locks below two FICO thresholds (680 and 640). For purchase mortgages (the two solid lines), there is no evidence of a drop in the percentage of low-FICO rate locks. There is a drop for refines, although this is typical during a refinancing boom because high-credit-score borrowers have a greater propensity to refinance when rates fall (e.g., Keys et al., 2016)

This evidence suggests that heightened individual default risk is not an important reason for the high markups in the prime conforming mortgage market during the pandemic. Default risk is more important for credit supply in the high-risk FHA market, however, as we show in Section VI.

V.B Macroeconomic and Health Shocks

Although we find little role for individual default risk, perhaps intermediation markups incorporate a more general premium due to the macroeconomic and health shock associated with the virus. In such a case, we might nevertheless expect heterogeneity, but primarily across locations, depending on how severely they were affected by the spread of the pandemic and the decline in economic activity.

We examine variation in locked rates (controlling for borrower and loan characteristics and upfront points) across the 100 most populous metro areas in Table 3. We regress loan-level interest rates from 1.1 million conventional conforming loans locked over the period November 2019 to August 2020 on metro area fixed effects, loan characteristics (loan-to-value ratio and credit score) interacted with week locked, and different proxies for how strongly a metro area was affected by COVID, in terms of the economic and health impact.

The first variable we try is COVID-19 cases per 1,000 metro area residents in the previous calendar month. Since this variable equals 0 everywhere prior to February 2020, the preceding months provide our “pre-period.” In fact, higher local case numbers are associated with slightly lower mortgage interest rates (column 1). The effect is extremely small, however—a one-standard deviation in case rate is associated with only a 0.3bp drop in mortgage rates. Results are similar if we instead use a dummy identifying the metro areas in the top quartile of cases per capita in the month (column 2).
Next we study the effect of the economic shock. Job losses, measured as the standardized year-over-year change in the local unemployment rate, are positively correlated with mortgage rates, although again the effect is not economically meaningful. A one-standard-deviation-increase in the unemployment rate is associated with a 1.2-basis-point-increase in mortgage rates. The aggregate increase in unemployment (from 3.5% to a peak of 14.8% nationally) would correspond to 2.7 standard deviations, or an impact on rates of about 3 basis points.\footnote{Our sample in Table 3 runs through August 2020. We choose to focus on the early part of the pandemic, when the primary-secondary spread is at its largest and the unemployment rate was high, to gauge an upper-bound on the impact of unemployment. The unemployment effect is even smaller if we extend the sample through the end of 2020.}

\section*{V.C Competition}

Table 3 also includes regressions to examine whether imperfect competition may help explain the rise in markups, motivated by Scharfstein and Sunderam (2016) who find lower mortgage rate pass-through in concentrated markets. Using two measures of market concentration interacted with a COVID-period dummy (= 1 from March 14, 2020 onward), we find no evidence that concentration reduced pass-through of lower rates during this episode. In column 4 of Table 3, the measure of concentration is the the share of mortgages originated in 2019 in metro area \( m \) by that area’s top four lenders, while in column 5 it is the local Herfindahl-Hirschman Index (HHI).\footnote{Both market concentration measures are derived from HMDA data for 2019, and standardized to have mean zero and standard deviation of one.} Neither interaction term is statistically significant, and the confidence bounds exclude any economically significant effect.\footnote{As can be seen in column 6, the conclusions in Table 3 remain similar if we consider a multivariate specification including interactions for the virus spread, unemployment and concentration together. Furthermore, in Internet Appendix Table A.4 we estimate the same models on an alternative dataset of originated conventional conforming loans, the McDash data. Again we find little relationship between either virus spread or market concentration and interest rates. The effect of unemployment and rates is also insignificant (with a negative point estimate).}

We consider the possibility that the pandemic itself reduced competition and thereby led to higher markups. Detailed updated measures of local concentration are not yet available, but national data provide no support for this hypothesis—in fact, the market share of the largest lenders if anything decreased in Q2 and Q3 of 2020, as we document in Internet Appendix Figure A.19 based on data from Inside Mortgage Finance.

In short, the rise in mortgage spreads during the pandemic is a national phenomenon,
and is not significantly related to the degree of virus spread, the depth of the economic crisis, or local market concentration. Consistent with these findings, Internet Appendix Figure A.20 shows that although mortgage rates do vary across metro areas, the differences are generally small, and between early 2019 and late 2020 the rank ordering of metro areas is quite persistent.40

V.D Shopping

Even if there are many lenders, each originator may enjoy market power if borrowers do not search extensively (e.g., Wolinsky, 1986). It is also possible that borrowers search less actively during refinancing booms, because they do not need to scour the marketplace to beat their current rate, which could increase lenders’ bargaining power.41 However, search activity in the mortgage market appears to have been extremely high during the 2020 pandemic episode. Google Trends data in panel A of Figure 7 indicate that web searches for refinance-related terms spiked in March and remained elevated thereafter. As shown in panel B of Figure 7, borrower search activity is 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.

Also speaking against a “low search intensity” hypothesis, servicer retention—the share of borrowers refinancing with their existing lender—decreased during the pandemic. In 2020:Q3, only 18 percent of borrowers who refinanced remained with their prior lender, the lowest rate for at least 15 years (Black Knight Financial Services, 2020).

VI Credit Supply in Riskier Market Segments

So far our analysis has focused on prime conforming mortgages. We now turn to other segments—the FHA market and the jumbo market—which present additional risk and complexity for intermediaries. Studying these riskier segments and comparing them to the conforming market sheds light on two questions: (1) Did the spike in forbearance and default risk reduce credit supply for the riskiest loans, and loans not eligible for govern-

40 The figure shows the average offered mortgage rates (from Optimal Blue Insight) on conventional conforming loans from the metros contained in the Case-Shiller 20 City Composite Home Price Index. Most of the metro area series are located close to the mean, and they rise and fall mostly in parallel.

41 See Bhutta et al. (2021) for some direct evidence on this point.
ment guarantees? (2) Did Federal Reserve policy intervention through the resumption of MBS quantitative easing support mortgage credit supply?

VI.A Default Risk and Credit Guarantees

VI.A.1 The FHA Market

We previously showed that the rise in forbearance and delinquency risk had little effect on conforming mortgage rates. But now we revisit this question for the FHA market, where mortgage intermediaries are significantly more exposed to default risk. This is because FHA borrowers default at much higher rates, and because institutional features of the FHA market shift more risk to the lender and servicer (Kim et al., 2018). For instance, servicers are obligated to advance payments on delinquent mortgages until termination or modification, and face significant delays before being reimbursed. The liquidity risk of servicing advances is particularly acute for the nonbank mortgage companies which now dominate FHA lending, because these nonbanks are financed by short-term debt and cannot issue insured deposits or access government liquidity backstops.

First we estimate cross-sectional differences in interest rates between FHA borrowers with lower versus higher default risk. We proceed using the same methodology as in Section V.A, first analyzing interest rates on mortgage offers and rate locks, and then studying quantities. For interest rates, we focus on the rate difference between borrowers with a credit score of 640 versus 680. 680 is a typical credit score for FHA loans (roughly at the 60th percentile in the first quarter of 2020), while 640 is roughly at the 20th percentile.

42 FHA borrowers are typically lower-income households and/or first-time home buyers. 15.7% of FHA loans were delinquent as of June 2020, compared to only 6.7% of conventional loans. (Source: 2020:Q2 MBA delinquency survey).

43 The FHA servicer is also not fully compensated for foreclosure costs; Tozer (2019) estimates that issuers bear around $10,000 in uncompensated costs per FHA claim. During the pandemic, Fannie Mae and Freddie Mac mitigated servicer liquidity risk by limiting advances on loans in forbearance to four months. No similar cap was established for FHA loans or other mortgages securitized through Ginnie Mae, although 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. The FHA also created a temporary liquidity facility for servicers due to concerns about liquidity risk.

44 Urban Institute (2021) calculates that 90% of Ginnie Mae mortgages were originated by nonbanks in December 2019, and the nonbank share increased even further to 93% by December 2020.

45 See Internet Appendix Figure A.17 for the evolution of the credit score distribution of FHA originations over 2019-2020. Other assumptions for the offer data are that we study 30-year FRMs with zero points, LTV = 95-97 percent (which is by far the most common in the FHA segment), and DTI of 36, for a home purchase.
Results in Figure 9 show a significant rise in the interest-rate premium associated with the riskiest FHA borrowers. Panel A traces the evolution of the FICO 640-680 interest rate spread in the offer data. The spread is stable at about 20bp prior to the pandemic, but rises sharply beginning in April, after the passage of the CARES Act and surge in forbearance-related delinquency. The spread peaks at around 70bp in June, 50bp above pre-pandemic levels. The spread then declines and displays some volatility, but remains elevated through to December. The low-FICO spread also increases in the locks data (panel B of Figure 9), following a similar pattern. The peak increase is only about 25bp, however, compared to around 50bp in the offer data.46

Data on quantities are also consistent with a decline in credit supply to high-risk FHA borrowers. Panel C of Figure 9 shows that the number of lenders offering FHA mortgages drops by a quarter for all credit scores during the market volatility in March. But in the highest risk segment (640 FICO) the number of lenders then falls further in April, to half the pre-pandemic level, even though lenders return to the market for lower risk loans. Lenders re-enter the FICO 640 segment later in 2020, although some remain unwilling to offer credit to these riskier borrowers. Similarly, Panel D shows that the share of FHA purchase rate locks to borrowers with FICO < 640 drops from around 30% before the pandemic to less than 15% in April, coincident with the spike in rate spreads and drop in the number of low-FICO FHA lenders.47 Notably there is no similar decline for FHA refinances, which may reflect that for an FHA issuer, refinancing an existing customer does not present additional liquidity or credit risk, since they are already responsible for advancing payments if the borrower defaults.48

So far we have focused on variation in risk within the FHA market. Figure A.3 in the Internet Appendix instead examines whether the intermediation mark ups increased more

46This 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 presented in the following section.

47As the figure shows, the fraction of loans to <680 FICO borrowers also declines but by a smaller amount. We also find similar patterns in lending shares using McDash origination data—see Figure A.17 in the Internet Appendix. The timing of the decline of low-credit-score shares is less sharp in McDash than in Optimal Blue, which likely reflects the variable time lag between the lock date and origination date (recalling that McDash only reports the latter).

48In 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 which waives many requirements including the need to conduct a property appraisal. Thus, operational issues related to the pandemic would thus disproportionately affect the FHA purchase market.
for FHA loans than for conforming mortgages. We indeed find that both the primary-secondary spread and gain-on-sale increased by a larger amount for FHA mortgages, consistent with an amplification of the risk premium associated with FHA lending.

VI.A.2 The Jumbo Market

Although jumbo borrowers are typically creditworthy, high-income households, jumbos are comparatively risky for lenders and investors because they are ineligible for agency securitization and thus do not carry government-backed credit guarantees. Comparing the jumbo and conforming markets therefore sheds light on whether these guarantees helped stabilize credit supply during the pandemic.

We use Optimal Blue data to estimate the interest rate spread on jumbo mortgages relative to smaller but otherwise identical conforming mortgages, following our earlier methodology. Results are presented in Figure 10.

Panel A plots the jumbo-conforming spread for offer rates on a prime mortgage with LTV of 80 and credit score of 750. Prior to the pandemic, jumbos carry an interest rate premium of 10-25bp. This spread then increases sharply, to 80-100bp between April and August, before declining to about 50bp by the end of 2020. The prime jumbo-conforming spread estimated based on rate locks (Panel B) follows a similar pattern, from 0-10bp before the pandemic to an average of 40-50bp from April-August, followed by a decline to around 30bp by December.

Panel B of Figure 10 also plots the estimated interest rate premium on “superconforming” (also known as “conforming jumbo”) mortgages. These are loans which exceed the national conforming loan limit but remain eligible for agency securitization because the property is located in a “high-cost” county with a higher limit (Vickery and Wright, 2013). As we discuss below, superconforming mortgages are somewhat less liquid, and also less likely to be purchased by the Federal Reserve in its quantitative easing program. Including a vector of superconforming × time dummies in the rate locks regression model,

49Most jumbo mortgages are ultimately held in portfolio by banks. There is also a modest amount of non-agency jumbo securitization.

50We also observe a rise in the jumbo-conforming spread during the pandemic using two alternative data sources, from Mortgage News Daily and the Mortgage Bankers Association—see Figure A.11 in the Internet Appendix. Furthermore, in the Insight data on offers, the increase in the jumbo-conforming spread is similarly large if we look at 5/1 ARMs.
we find that the superconforming-conforming spread does indeed increase early in the pandemic, from around 10-20bp to 30-35bp, coincident with the significant Fed MBS QE during this period. The spike in the superconforming spread is not permanent, however; it falls back to near-normal levels by mid-June. We return to this result in Section VI.B.

We also find a reduction in jumbo lending. Panel C of Figure 10 shows that the number of lenders offering jumbos to FICO 750 borrowers on the Optimal Blue platform drops by more than half in the early stages of the pandemic, before slowly recovering to a level about 20% below pre-pandemic levels by December. For lower FICO borrowers (680 and 640) the number of active lenders collapses almost to zero. By contrast, the number of lenders in the conforming market remains fairly steady, as shown earlier in Figure 6. The dollar volume of jumbo rate locks also declines by about half as a fraction of all rate locks, both for purchase mortgages and refinancings (panel D), before recovering later in 2020.

Although this evidence is consistent with a negative supply response, an important caveat is that Optimal Blue primarily reflects mortgages originated by nonbanks. Banks have a stronger presence in the jumbo market than other segments of the mortgage market; furthermore, a number of large banks stopped purchasing jumbos from nonbanks during the pandemic (Eisen, 2020). A potential concern is that the drop in quantities we observe simply reflects substitution in jumbo lending from nonbanks to banks.

To obtain a more representative picture of the jumbo market, we turn to McDash loan-level data, which has good coverage of both bank and nonbank lending. We estimate linear probability models in which the dependent variable equals one for a jumbo loan, using McDash loans within a 10% window either side of the applicable conforming loan limit (the national limit, or the relevant higher local limit for mortgages in high-cost counties). The key explanatory variable is a pandemic dummy set equal to 1 from April 2020 onwards.

Results reported in panel A of Table 4 show that the fraction of jumbo loans drops significantly during the pandemic, by around 7-8 percentage points compared to a sample average of 16 percentage points. These results are fairly consistent across purchase mortgages and refinancings and of similar magnitude regardless of whether we control for loan characteristics including zip-code fixed effects, debt-to-income, property value, loan-to-value and credit score.\footnote{See table notes for full list of controls. In Internet Appendix D we trace out the dynamics of the jumbo share.
VI.B Quantitative Easing

The absence of a government-backed credit guarantee is the key differentiator of jumbo mortgages from conforming loans, but another important factor is that the Federal Reserve resumed active QE purchases of agency MBS starting in March of 2020 as part of its policy response to the pandemic. The Fed rapidly increased the size of its MBS portfolio during the early months of the crisis, from $1.37tr at the start of March to $1.90tr by the start of July.\(^{52}\) Given that the Fed does not purchase jumbo mortgages, this raises the question of whether the above results partially reflect positive effects of Fed QE on the supply of credit in the conforming market. Understanding the effects of Fed QE on mortgage rates and quantities during the pandemic is also of independent interest.

The earlier time-series evidence in Figure 2 suggests that the resumption of Fed QE in mid-March does reduce mortgage rates. OAS drops by around 40bp right after QE begins, and option cost also declines due to a drop in interest rate volatility. These changes are almost exactly offset by a rise in the primary-secondary spread, however, leaving the mortgage-Treasury spread almost unchanged.

A different way to parse out whether Fed QE helped lower mortgage rates, which does not just rely on time-series variation, is to study superconforming mortgages exceeding the national conforming limit.\(^{53}\) Superconforming mortgages are less likely to be purchased by the Fed because the Fed purchases agency MBS through the “to-be-announced” or TBA market, and agency MBS 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 data on the Fed’s MBS security holdings, we confirm that the probability an agency mortgage ends up in a pool in the Fed’s MBS portfolio does indeed drop sharply just above the national conforming limit, declining by about 40%.

In panel B of Table 4, we restrict the sample to high-cost counties and study shifts in lending around both the national conforming loan limit and the higher local limit, to


\(^{53}\)Fannie Mae and Freddie Mac are not permitted to purchase or securitize mortgages exceeding the relevant conforming loan limit. A 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. Superconforming mortgages are loans between the national limit and these higher local limits.
disentangle the effects of Fed QE from credit guarantees. Both forces appear to have promoted credit supply; columns 1-3 indicate a reduction in the share of superconforming loans just above the national limit which have lower eligibility for Fed QE, while columns 4-6 show an additional drop in lending above the relevant local conforming limit. The latter estimates are quantitatively larger relative to the sample mean, however, suggesting that credit guarantees were relatively more important than QE in bolstering credit supply in the agency segment of the market.

Figure A.21 in the Internet Appendix further explores the dynamics of these two factors, finding that the loan volume effects around the national limit (which reflect only QE) are significant in the early stages of the pandemic, but are less persistent than the effects at the local limit. Consistent with this finding, our interest rate estimates in Figure 10 imply that the superconforming-conforming spread is elevated but only through to June 2020, while the jumbo-conforming spread remains high through to at least December.

To sum up, these results suggest that Fed QE did reduce mortgage rates and expand credit supply during the pandemic, but that the direct effects of QE may have faded after a few months. Our estimates do not reflect the full general-equilibrium effects of QE, however, and thus should be interpreted accordingly.

VI.C Summing Up

The results in this section indicate that government-backed credit guarantees helped support mortgage lending during the pandemic, as evidenced by a relative contraction in supply (higher interest rates, lower volume) in the jumbo mortgage market which does not feature guarantees. Our analysis of the FHA market, however, also shows that public guarantees are not always sufficient to fully insulate lenders against default risk — we find evidence of a contraction in supply for the highest-risk borrowers even in the government-guaranteed part of the market. Lastly, using the fact that superconforming mortgages are less likely to be purchased by the Fed, we show that Federal Reserve quantitative easing supported credit supply, particularly in the early months of the pandemic.
VII Conclusion

The mortgage market experienced a historic boom in 2020, with record origination volumes and lender profits. While many borrowers also benefited from record-low mortgage rates, the evidence presented in this paper suggests that intermediation frictions limited the pass-through of lower interest rates to borrowers. Mortgage demand shocks are historically associated with changes in markups in the mortgage market, but this historical relationship accounts for only part of the rise in intermediation markups during the pandemic. Several pieces of evidence indicate that operational frictions have reduced the elasticity of mortgage supply: expanding capacity was more difficult than usual, keeping lender markups high. At the same time, there was a significant shift in market share toward more elastic “fintech” lenders, especially for purchase mortgages.

Figure 3B shows that during the last three quarters of 2020, intermediaries collected about five percent of a mortgage’s balance for the service of linking borrowers with savers, or USD 162bn in total. One surprising question is whether for rate-and-term refinances, it makes sense for intermediaries to collect anything. From the standpoint of an individual lender making a loan to a new borrower, careful underwriting makes sense as the lender is taking on a new risk. However, from the standpoint of the economy as a whole, a rate-and-term refinance uniformly lowers the likelihood of default, even if the lender expends no effort underwriting the mortgage. The costs of socially unnecessary underwriting cascades across the economy. For some borrowers, the increase in costs makes refinancing uneconomic. For borrowers who do refinance, the reduction in rates is smaller. Then, capacity constraints, which we document to be particularly binding during the pandemic episode, mean that rate-and-term refinance underwriting starves resources from the more socially useful task of underwriting purchase and cash-out refinances. Our findings, therefore, reinforce arguments for both streamlined refinances and automatically refinancing mortgage products. Much like during the financial crisis, such products would have substantially strengthened the transmission of low interest rates to households during the pandemic.

Like the experience of the 2008 financial crisis, government credit guarantees have played an important role in stabilizing credit supply, reflected in a larger increase in mortgage interest rate spreads in the jumbo segment of the market where such guarantees are absent. However, our results also highlight the fact that such guarantees have not fully
insulated lenders from risk, and that this residual exposure has been priced into mortgage interest rates at least for some borrowers. Our results are suggestive of some surprising “barbell” distributional effects of the pandemic, with low-income FHA borrowers and high-income jumbo borrowers experiencing a larger deterioration in credit availability than middle-class borrowers.
References


Figure 2: Accounting for the Rise in the Mortgage-Treasury Spread During Two Crises

A. COVID-19 Pandemic (2020)


Decomposition based on the methodology described in Section III.A. Data sources: Freddie Mac PMMS, Optimal Blue, J.P. Morgan 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. Data sources: Freddie Mac PMMS, Optimal Blue, J.P. Morgan Markets, MBA (via Haver Analytics).

Notes: Vertical line represents the declaration of a national state of emergency in March 13th, 2020.
Figure 4: Lenders’ Reported Net Production Income
A. In basis points

B. Multiplied by average originated loan volume

Figure 5: Intermediation Markups and the Demand for Refinancing

A. Prim.-Sec. Spread vs. Proxy for Refi Incentives

B. Prim.-Sec. Spread vs. Application Volume

C. Gain-on-Sale vs. Proxy for Refi Incentives

D. Gain-on-Sale vs. vs. Application Volume

Notes: numbers next to red squares denote the calendar month in 2020. The trend line and the 90% confidence intervals are estimates using data 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 6: Credit Supply in the Conforming Market

A. Offer rate spread: FICO 680 vs 750

B. Locks rate spread: FICO 680 vs 740+

C. Number of lenders posting offers

D. Distribution of rate locks by credit score

Notes: Measures of credit supply computed using the methodology described in Section V.A. Vertical line represents the declaration of a national state of emergency in March 13th, 2020. Data source: Optimal Blue
Figure 7: Web Searches for Mortgage Refinancing

A. Search index for refinance related terms

![Search Index Graph]

Notes: 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.

B. Google searches vs. the refinance incentive

![Search vs. Incentive Graph]

Notes: 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.
Figure 8: Mortgage Loan Officer Job Postings and Employment Growth

A. Mortgage Loan Officer Postings and Employment

```

0.5 1.0 1.5 2.0 2.5 3.0 3.5 4.0

In thousands

Actual Employment
Postings per 100 Employees
Counterfactual employment
```

B. Predicted versus Actual Employment Growth

```
-0.03 -0.02 -0.01 0.00 0.01 0.02 0.03 0.04

Predicted Employment Change
Actual Employment Change
```

Panel A shows mortgage employment and postings per employee from the BLS Establishment Survey and Burning Glass Technologies. Panel B compares predicted and actual values from the regression

\[
\log MLO_{t+1} - \log MLO_t = \alpha + \beta_1 p_t + \beta_2 p_{t-1} + \beta_3 p_{t-2} + \epsilon_t
\]

where \(MLO_t\) and \(p_t\) correspond to mortgage employment and postings per employee in Panel A. Baseline regression is run on data from 3/2012 to 2/2020. Dots labeled “COVID” are out-of-sample predictions for 3/2020 to 12/2020. Counterfactual employment in Panel A uses the predicted growth rates from the regression to compute employment in the COVID period.
Figure 9: Credit Supply in the FHA Market

A. Offer rate spread: FICO 640 vs 680

B. Rate lock spread: FICO 640 vs 680

C. Number of lenders posting offers

D. Distribution of rate locks by credit score

Notes: Measures of credit supply computed using the methodology described in Section V.A. Vertical line represents the declaration of a national state of emergency in March 13th, 2020. Data source: Optimal Blue
Figure 10: Credit Supply in the Jumbo Market

A. Offer rate jumbo-conforming spread

B. Rate lock spreads

C. Number of lenders posting offers

D. Share of jumbo rate locks

Notes: Measures of credit supply computed using the methodology described in Section V.A. Vertical line represents the declaration of a national state of emergency in March 13th, 2020. Data source: Optimal Blue
Table 1: Intermediation Markups and Mortgage Demand

<table>
<thead>
<tr>
<th></th>
<th>(1) Primary-Secondary Spread (bp)</th>
<th>(2) Gain-on-Sale ($ per $100 face value)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Refi incentive (WAC - 10 Year Treasury)</td>
<td>21.71*** (1.996)</td>
<td>0.655*** (0.0636)</td>
</tr>
<tr>
<td>MBA Applications Index</td>
<td>0.071*** (0.0109)</td>
<td>0.00192*** (0.000369)</td>
</tr>
<tr>
<td>March - May dummy</td>
<td>76.81*** (10.45)</td>
<td>1.053*** (0.270)</td>
</tr>
<tr>
<td>June - August dummy</td>
<td>85.77*** (5.268)</td>
<td>1.383*** (0.154)</td>
</tr>
<tr>
<td>September - October dummy</td>
<td>52.19*** (7.214)</td>
<td>1.285*** (0.189)</td>
</tr>
<tr>
<td>November - December dummy</td>
<td>37.67*** (3.042)</td>
<td>1.317*** (0.114)</td>
</tr>
<tr>
<td>Constant</td>
<td>70.88*** (4.621)</td>
<td>1.484*** (0.188)</td>
</tr>
<tr>
<td>N</td>
<td>466</td>
<td>466</td>
</tr>
<tr>
<td>Mean Y</td>
<td>125.28</td>
<td>3.04</td>
</tr>
<tr>
<td>R2</td>
<td>0.91</td>
<td>0.78</td>
</tr>
<tr>
<td>RMSE</td>
<td>9.91</td>
<td>0.39</td>
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<tr>
<td>RMSE (no dummies, -Feb. 2020)</td>
<td>8.93</td>
<td>0.38</td>
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</table>

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). Newey-West standard errors (6 lags) in parentheses. * $ p < 0.10, * * p < 0.05, ** p < 0.01, *** p < 0.001.
Table 2: Changes in Fintech Mortgage Lending During the Pandemic

<table>
<thead>
<tr>
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<th>Purchase Mortgages</th>
<th>Refinancings</th>
<th>All Loans</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Pandemic</td>
<td>2.74***</td>
<td>2.17***</td>
<td>1.48***</td>
</tr>
<tr>
<td></td>
<td>(0.28)</td>
<td>(0.27)</td>
<td>(0.26)</td>
</tr>
<tr>
<td>Pandemic × FICO&lt;680</td>
<td>2.67***</td>
<td>4.04***</td>
<td>2.10***</td>
</tr>
<tr>
<td></td>
<td>(0.26)</td>
<td>(0.34)</td>
<td>(0.21)</td>
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Num obs. 5147358 5147358 5147358 5473513 5473513 5473513 10620871 10620871 10620871
Mean of dep. var. 10.74 10.74 10.74 27.14 27.14 27.14 19.19 19.19 19.19
Loan controls N Y Y N Y Y N Y Y
FICO<680 dummy N N Y N N Y N N Y

Notes: Fintech lenders are identified based on the classification in Fuster et al. (2019). Pandemic dummy = 1 if estimated origination date is April 2020 or later. Loan controls include: state dummies; government agency dummies (Fannie Mae, Freddie Mac, FHA, VA, RHS and Section 184 Indian home); debt-to-income (DTI), DTI², loan-to-value (LTV), LTV², credit score, credit score², loan principal, log(loan principal), number of borrowers, and a first-time homebuyer dummy. Specifications including a FICO<680 interaction term also include an uninteracted FICO<680 dummy in the controls. Sample period is January 2019 to December 2020. Linear probability model estimated using eMBS loan-level data on mortgages securitized by Fannie Mae, Freddie Mac and Ginnie Mae. Sample includes nonbank mortgages only. Standard errors clustered by state. \( \sim p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001. \)
Table 3: Metro Area Differences in Conventional Conforming Mortgage Rates (%) in Optimal Blue Locks

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<tbody>
<tr>
<td><strong>Virus spread:</strong></td>
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<td></td>
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<tr>
<td>COVID cases per capita</td>
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<td>(0.0008)</td>
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<tr>
<td>Dummy: MSA in top quartile</td>
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<td>-0.0183***</td>
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<td>(0.0051)</td>
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<tr>
<td><strong>Unemployment:</strong></td>
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<tr>
<td>Year-over-year change in U.R.</td>
<td>0.0112*</td>
<td>0.0118*</td>
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<tr>
<td></td>
<td>(0.0054)</td>
<td>(0.0051)</td>
<td></td>
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<tr>
<td><strong>Market concentration:</strong></td>
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<td></td>
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</tr>
<tr>
<td>COVID × top 4 share</td>
<td>0.0025</td>
<td>0.0001</td>
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<tr>
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<td>(0.0041)</td>
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<td></td>
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<tr>
<td>COVID × HHI</td>
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<td>Loan controls × week FE</td>
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<tr>
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<td>1,130,086</td>
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<td>1,130,086</td>
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<td>1,130,086</td>
</tr>
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</table>

Data Sources: Optimal Blue locks data, *New York Times* COVID data, Bureau of Labor Statistics unemployment data, and Home Mortgage Disclosure Act data. Notes: Sample includes loans locked from November 2019 to August 2020 in the 100 largest CBSAs. Standard errors in parentheses, clustered at CBSA level. COVID cases per 1,000 are lagged one month. The top 4 lenders’ market share, HHI, and year-over-year unemployment are all standardized with mean of 0 and standard deviation of 1. Mortgage interest rates are adjusted for points paid by borrower (credits received from lender). Additional controls include CBSA-level fixed effects, as well as lock week interacted with loan characteristics: 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). ∼ p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001.
Table 4: Changes in Jumbo Lending During the Pandemic

A. Change in jumbo share

Dependent Variable = 100 if mortgage balance exceeds conforming limit

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(0.166)</td>
<td>(0.149)</td>
<td>(0.204)</td>
<td>(0.165)</td>
<td>(0.144)</td>
<td>(0.117)</td>
</tr>
<tr>
<td>N</td>
<td>270292</td>
<td>267645</td>
<td>299819</td>
<td>297252</td>
<td>589233</td>
<td>586663</td>
</tr>
<tr>
<td>Mean Y</td>
<td>15.06</td>
<td>15.09</td>
<td>14.40</td>
<td>14.44</td>
<td>15.13</td>
<td>15.14</td>
</tr>
<tr>
<td>Origination type</td>
<td>Purchase</td>
<td>Purchase</td>
<td>Refinance</td>
<td>Refinance</td>
<td>All</td>
<td>All</td>
</tr>
<tr>
<td>Loan controls</td>
<td>N</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
</tr>
</tbody>
</table>

B. Change in jumbo and super-conforming share, high-cost areas only

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

<table>
<thead>
<tr>
<th></th>
<th>&gt; national CLL</th>
<th>&gt; local CLL</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
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<tr>
<td></td>
<td>(0.319)</td>
<td>(0.191)</td>
</tr>
<tr>
<td>N</td>
<td>152005</td>
<td>325164</td>
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<tr>
<td>Mean Y</td>
<td>35.59</td>
<td>27.02</td>
</tr>
<tr>
<td>Origination type</td>
<td>Purchase</td>
<td>Refinance</td>
</tr>
<tr>
<td>Loan controls</td>
<td>Y</td>
<td>Y</td>
</tr>
</tbody>
</table>

Notes: Linear probability model, estimated using Black Knight McDash loan-level 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). In panel B, sample is restricted to “high-cost” counties where the county-level CLL exceeds the national CLL. Pandemic dummy = 1 if origination date is April 2020 or later. Loan controls include: zipcode dummies, debt-to-income (DTI), DTI$^2$, loan-to-value (LTV), LTV$^2$, credit score, credit score$^2$, appraisal amount, and log(appraisal amount). Sample period is January 2019 to October 2020. ∼ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Robust standard errors in parentheses clustered at zip code level.
Internet Appendix for
“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 Intermediation Markups

A.1 Alternative Measures for Conventional Conforming Market

Figure A.1: Primary-Secondary Spread Using the Current Coupon: Conforming Market

Figure A.2: Evolution of Originator Profits and Unmeasured Costs (OPUC)


Figure A.3: OPUC and Mortgage Demand

OPUC vs. Refinance Incentive

OPUC vs. Applications

A.2 FHA Mortgages

Figure A.4: Comparing Measures of Primary-Secondary Spread: FHA Market

Figure A.5: Comparing Measures of Gain-on-sale: FHA Market

Notes: Computed based on the methodology described in Section III.C. Vertical line represents the declaration of a national state of emergency in March 13th, 2020. Data sources: Optimal Blue, J.P. Morgan Markets, MBA (via Haver Analytics).
A.3 Difference in Intermediation Markups between FHA and Conforming Market

Figure A.6: Primary-Secondary Spread: FHA - Conforming

Figure A.7: Gain-on-Sale: FHA - Conforming

Notes: Vertical line represents the declaration of a national state of emergency in March 13th, 2020. Data source: Optimal Blue, JP Morgan Markets, MBA (via Haver Analytics)
A.4 Evolution of Servicing Multiples

Figure A.8: Base Servicing Multiples for Conforming and FHA Mortgages

A. Conforming Mortgages

Data sources: SitusAMC for servicing multiples; Freddie Mac PMMS (panel A) and MBA (panel B) for mortgage rates. “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.
B Labor Market Frictions

B.1 Postings and Employment Growth

Table A.1 shows the relationship between job postings for mortgage loan officers and underwriters and employment growth in NAICS codes 522292 (real estate credit at non-bank financial intermediaries) and 52231 (mortgage and nonmortgage loan brokers). Model 1 estimates the relationship using pre-pandemic data only (March 2012 – February 2020). Model 2 adds the pandemic period (through December 2020) and includes a pandemic time dummy.

<table>
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<tr>
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<th>Employment Change</th>
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<tbody>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td>Job postings per 100 employees (_t)</td>
<td>0.0157**</td>
</tr>
<tr>
<td></td>
<td>(0.0053)</td>
</tr>
<tr>
<td>Job postings per 100 employees (_t-1)</td>
<td>0.0118**</td>
</tr>
<tr>
<td></td>
<td>(0.0044)</td>
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<tr>
<td>Job postings per 100 employees (_t-2)</td>
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<tr>
<td></td>
<td>(0.0055)</td>
</tr>
<tr>
<td>Pandemic</td>
<td>-0.0152***</td>
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<tr>
<td></td>
<td>(0.0044)</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.0233***</td>
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<tr>
<td></td>
<td>(0.0062)</td>
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<tr>
<td>N</td>
<td>96</td>
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<tr>
<td>Mean Y</td>
<td>0.0023</td>
</tr>
<tr>
<td>Adj. R2</td>
<td>0.2156</td>
</tr>
</tbody>
</table>

Data sources: Burning Glass Technologies and Bureau of Labor Statistics Current Employment Statistics data. Newey-West standard errors with 4 lags in parentheses. \(~ p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001.~
B.2 Personnel Expenses

Figure A.9 is based on the MBA Quarterly Performance Report and plots the relationship between the number of loans the average mortgage bank originates in a quarter and its personnel expenses, expressed in bps of the total amount of loans originated.\(^1\) Since some personnel expenses are fixed, we expect a decreasing relationship, and the black dots along with the grey line show that over 2015-2019, the relationship was indeed strongly and approximately linearly decreasing.

The first quarter of 2020 still appears closely in line with the relationship over the previous years. However, from 2020:Q2 onward, and especially in Q3 and Q4, personnel expenses appear unusually high: despite large increases in loan originations relative to Q2, personnel expenses \textit{increased} over those two quarters. This is consistent with the tight labor market for loan officers, underwriters, processors etc. leading to increases in compensation in order to attract new workers or prevent poaching by competitors.

Quantifying the “excess” expense is not straightforward and depends on the functional form assumption. In columns 1 and 2 of Table A.2, we control for originated loans linearly (either based on the number of loans or the volume in USD), like in the figure. We add four dummies for the four quarters of 2020, which measure the excess in a quarter relative to what would be expected based on the 2015-2019 data. The coefficients for Q3 and Q4 are highly significant and range from 58 to 98 bps—a very large effect.

In columns 3 and 4, we instead use a functional form that appears more appropriate in a situation where part of the cost is strictly fixed, using the inverse of the loan volume as a regressor. Coefficients on the Q3 and Q4 dummies are again strongly significant, but of more modest (though still meaningful) size, ranging from 12 to 29 bps.

\(^1\)We only incorporate data from 2015 onward, since over the preceding years, there was a steady upward trend in expenses for a given level of originations, suggesting cost increases in the wake of the financial crisis (Fuster et al., 2017).
Figure A.9: Personnel Expenses vs. Origination Volumes

Data source: Mortgage Bankers Association Quarterly Performance Report.
Table A.2: **Regression Evidence on Excess Personnel Expenses (in bps) of Mortgage Banks in 2020**

<table>
<thead>
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<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Avg. originated loans</td>
<td>-0.036***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Avg. originated loans (Mio USD)</td>
<td>-0.132***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.016)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>-1/Avg. originated loans</td>
<td>-185283.904***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(25269.144)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>-1/Avg. originated loans (Mio USD)</td>
<td>-44101.600***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(4743.749)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2020:Q1</td>
<td>-2.563</td>
<td>5.987**</td>
<td>-1.885</td>
<td>5.089**</td>
</tr>
<tr>
<td></td>
<td>(3.027)</td>
<td>(2.584)</td>
<td>(2.745)</td>
<td>(1.831)</td>
</tr>
<tr>
<td></td>
<td>(6.417)</td>
<td>(6.091)</td>
<td>(3.676)</td>
<td>(2.586)</td>
</tr>
<tr>
<td>2020:Q3</td>
<td>57.994***</td>
<td>71.610***</td>
<td>14.272***</td>
<td>18.113***</td>
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<td></td>
<td>(11.620)</td>
<td>(10.864)</td>
<td>(4.904)</td>
<td>(3.454)</td>
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<tr>
<td>2020:Q4</td>
<td>77.473***</td>
<td>97.695***</td>
<td>24.756***</td>
<td>29.208***</td>
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<tr>
<td></td>
<td>(13.169)</td>
<td>(12.977)</td>
<td>(5.186)</td>
<td>(3.739)</td>
</tr>
<tr>
<td>Constant</td>
<td>300.235***</td>
<td>291.949***</td>
<td>133.866***</td>
<td>136.158***</td>
</tr>
<tr>
<td></td>
<td>(12.881)</td>
<td>(10.715)</td>
<td>(9.798)</td>
<td>(6.735)</td>
</tr>
<tr>
<td>Avg. Y</td>
<td>212.41</td>
<td>212.41</td>
<td>212.41</td>
<td>212.41</td>
</tr>
<tr>
<td>SD Y</td>
<td>19.93</td>
<td>19.93</td>
<td>19.93</td>
<td>19.93</td>
</tr>
<tr>
<td>Adj. R2</td>
<td>0.68</td>
<td>0.71</td>
<td>0.68</td>
<td>0.74</td>
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<td>Obs.</td>
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<td>24</td>
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</table>

Newey-West standard errors (3 lags) in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

C Market Share of Fintech Lenders

Figure A.10 displays estimated coefficients on the vector of monthly time dummies from a loan-level linear probability regression of whether the mortgage is originated by a fintech lender, along with 95 percent confidence intervals (based on standard errors clustered by state). The displayed values are normalized so that the fitted value equals the actual value in January 2020. The regression specification matches the models in Table 2, and controls for the loan and borrower characteristics are as listed in that table. The sample period is January 2019 to October 2020, and the data source is eMBS loan-level data on mortgages securitized by Fannie Mae, Freddie Mac and Ginnie Mae. The sample excludes bank loans.

Table A.3 presented below repeats the analysis from Table 2 retaining mortgages originated by banks in the sample. Bank lenders are identified by name in the eMBS data. Relaxing this sample restriction does not alter our main conclusions: (i) fintech lenders gain market share overall; and (ii) this increase is concentrated among mortgages which are more complex and time-intensive to underwrite, specifically purchase mortgages and mortgages to lower-credit-score borrowers.
Figure A.10: **Time-series of estimated fintech share after controlling for loan and borrower characteristics**

A. Fintech share: Purchase mortgages

B. Fintech share: Refinancings

C. Fintech share: All mortgages

Data source: eMBS.
Table A.3: Fintech lending during the pandemic: Sample retaining bank loans

<table>
<thead>
<tr>
<th></th>
<th>Purchase Mortgages</th>
<th>Refinancings</th>
<th>All Loans</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pandemic</td>
<td>2.50***</td>
<td>0.11</td>
<td>3.46***</td>
</tr>
<tr>
<td></td>
<td>(0.23)</td>
<td>(0.64)</td>
<td>(0.36)</td>
</tr>
<tr>
<td>Pandemic ×</td>
<td>2.11***</td>
<td>2.83***</td>
<td>1.07***</td>
</tr>
<tr>
<td>FICO&lt;680</td>
<td>(0.25)</td>
<td>(0.20)</td>
<td>(0.18)</td>
</tr>
</tbody>
</table>

Num obs. 6910501 6910501 6910501 7779519 7779519 7779519 14690020 14690020 14690020
Mean of dep. var. 8.00 8.00 8.00 19.10 19.10 19.10 13.88 13.88 13.88
Loan controls N Y Y N Y Y N Y Y
FICO<680 dummy   N N Y N N Y N N Y

Notes: Fintech lenders are identified based on the classification in Fuster et al. (2019). Pandemic dummy = 1 if origination month is April 2020 or later. Loan controls include: state dummies; government agency dummies (Fannie Mae, Freddie Mac, FHA, VA, RHS and Section 184 Indian home); debt-to-income (DTI), DTI^2, loan-to-value (LTV), LTV^2, credit score, credit score^2, loan principal, log(loan principal), number of borrowers, and a first-time homebuyer dummy. Specifications including a FICO<680 interaction term also include an uninteracted FICO<680 dummy in the controls. Sample period is January 2019 to December 2020. Linear probability model estimated using eMBS loan-level data on mortgages securitized by Fannie Mae, Freddie Mac and Ginnie Mae. Standard errors clustered by state. ∼ p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001.
D Additional Evidence on Jumbo Segment

Figure A.11: Jumbo-conforming spreads from other data sources

Notes: Vertical line represents the declaration of a national state of emergency in March 13th, 2020. Data source: Mortgage News Daily, Mortgage Bankers Association (via Haver Analytics)

D.1 Time-series Evolution of Jumbo Share in McDash Data

Figure A.12 displays estimated coefficients on the vector of monthly time dummies from a loan-level linear probability regression of whether a mortgage is a jumbo loan, along with 95 percent confidence intervals (based on standard errors clustered by zip code). Sample includes loans within 10% either side of the conforming limit applicable to each loan (either the national or county-level limit). Jumbo loans are defined as mortgages exceeding the conforming loan limit. The data source is Black Knight McDash.
Figure A.12: Time-series of jumbo share among loans within 10% of conforming limit

A. Purchase mortgages

B. Refinancings

C. All mortgages

Data source: Black Knight McDash
The Non-QM Market

In this section, we study changes in the supply of credit for non-qualified (“non-QM”) jumbo mortgages with debt-to-income (DTI) ratios exceeding 43%, which expose lenders to additional legal risk. Non-QM loans legally require the lender to properly verify and document that the borrower is capable of repaying the mortgage, the so-called “Ability-To-Repay” requirement. The non-QM market includes all jumbo mortgages with a back-end DTI ratio exceeding 43%, as well as certain other contract types (e.g., mortgages not requiring tax returns for income documentation). DeFusco et al. (2019) find that the Ability-To-Repay requirement reduces lending and increases mortgage interest rates above the DTI = 43% threshold.

We use Optimal Blue to analyze price and quantity for jumbos above and below a DTI of 43, using a methodology similar to what is shown in the main text. Specifically, in the Optimal Blue Insight data we compare rate offers on otherwise identical mortgages with a DTI of 44 compared to 43. In the locks data we restrict the sample to loans with DTI > 40, and then include a vector of DTI > 43 × time fixed effects to trace out the conditional rate premium associated with a non-QM mortgage. We also calculate the share of all jumbo rate locks made to borrowers with a DTI > 43.

The results presented in Figure A.13 show that the number of lenders serving the non-QM market drops by about 90% in March 2020, and offered interest rates spike by more than 100bp. The non-QM interest rate spread on jumbo rate locks remains fairly stable over the course of the pandemic, however, as does the non-QM share of all jumbo mortgage locks. Note that non-QMs represent only 3% of jumbos even before the pandemic.

One interpretation of this evidence is that specialist lenders remain active in the non-QM market and continue to lend, but non-specialists either exit or raise their offered interest rates. Non-QM lending drops in line with jumbo lending as a whole, but we find only mixed evidence of an amplified legal risk premium for non-QM loans.
Figure A.13: Credit Availability for non-QM Mortgages

Notes: Vertical line represents the declaration of a national state of emergency in March 13th, 2020. Data source: Optimal Blue
Figure A.14 below presents a binscatter plot of the proportion of mortgages that are 60+ days past due as of January 2020 and May 2020. Figure is based on Black Knight McDash (McDash) servicing data for mortgages originated since 2017. FHA loans are flagged based on the static loan type field in McDash. Figure A.15 shows the change in the delinquency rate from January to June.

As the figures show, delinquency rates have increased across the credit score distribution for GSE, FHA and portfolio loans. However the rise in delinquency rates is 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.

Figure A.14: Delinquency vs. Credit Score: Pre- vs. Post-pandemic

Data source: Black Knight McDash Data. 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.15: Delinquency vs. Credit Score: Pre- vs. Post-pandemic (Percentage Point Change)

Data source: Black Knight McDash Data. 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.
G Credit Score Distributions

Figure A.16: Credit Score Distribution: Conventional Conforming

Data source: Black Knight McDash Data. Note: Includes originations of 30-year, fixed-rate conventional mortgages made to owner-occupants, weighted by loan balance at origination.
Figure A.17: **Credit Score Distribution: FHA**

Data source: Black Knight McDash Data. Note: Includes originations of 30-year, fixed-rate FHA mortgages made to owner-occupants, weighted by loan balance at origination.
Figure A.18: **Credit Score Distribution: Jumbo**

Data source: Black Knight McDash Data. Note: Includes originations of 30-year, fixed-rate conventional mortgages made to owner-occupants, weighted by loan balance at origination.
Figure A.19: Market Concentration in the Conventional/Conforming Loan Market

Figure shows the quarterly market share (based on dollar volumes of originations) of the top $N$ firms over 2018:Q4 to 2020:Q3. Data source: Inside Mortgage Finance.
Figure A.20: 

Conforming Mortgage Rates for 20 CBSAs (Optimal Blue Insights data)

Data source: Optimal Blue
Figure A.21: Lending above national vs local conforming limit

(a) National conforming limit

(b) Local limit

Purchase mortgages:

Refinances:

All loans:

Data source: McDash.
Table A.4: Metro area differences in mortgage interest rates (%) in McDash: Conventional Conforming.

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Virus spread:</strong></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>COVID cases per capita</td>
<td>-0.0016**</td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td>(0.0006)</td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Dummy: MSA in top quartile</td>
<td>-0.0048∼</td>
<td>-0.0051*</td>
<td></td>
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<tr>
<td></td>
<td>(0.0025)</td>
<td>(0.0023)</td>
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<tr>
<td><strong>Unemployment:</strong></td>
<td></td>
<td></td>
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<td></td>
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</tr>
<tr>
<td>Year-over-year change in U.R.</td>
<td>-0.0038</td>
<td>-0.0024</td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td></td>
<td>(0.0048)</td>
<td>(0.0048)</td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td><strong>Market concentration:</strong></td>
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<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>COVID × top 4 share</td>
<td>-0.0042</td>
<td>-0.0043</td>
<td></td>
<td></td>
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</tr>
<tr>
<td></td>
<td>(0.0026)</td>
<td>(0.0027)</td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>COVID × HHI</td>
<td></td>
<td></td>
<td></td>
<td>-0.0002</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
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<td></td>
<td></td>
<td>(0.0028)</td>
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<td></td>
</tr>
<tr>
<td>Geographic FE</td>
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<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Loan controls × week FE</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>N</td>
<td>1,007,250</td>
<td>1,007,250</td>
<td>1,007,250</td>
<td>1,007,250</td>
<td>1,007,250</td>
<td>1,007,250</td>
</tr>
</tbody>
</table>

Data sources: Black Knight McDash data, New York Times COVID data, Bureau of Labor Statistics unemployment data, and Home Mortgage Disclosure Act data. Notes: Sample includes loans locked from November 2019 to August 2020 in the 100 largest CBSAs. Standard errors in parentheses, clustered at CBSA level. COVID cases per 1,000 are lagged one month. The top 4 lenders’ market share, HHI, and year-over-year unemployment are all standardized with mean of 0 and standard deviation of 1. Mortgage interest rates are adjusted for points paid by borrower (credits received from lender). Additional controls include CBSA-level fixed effects, as well as lock week interacted with loan characteristics: binned credit 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). ∼ p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001.