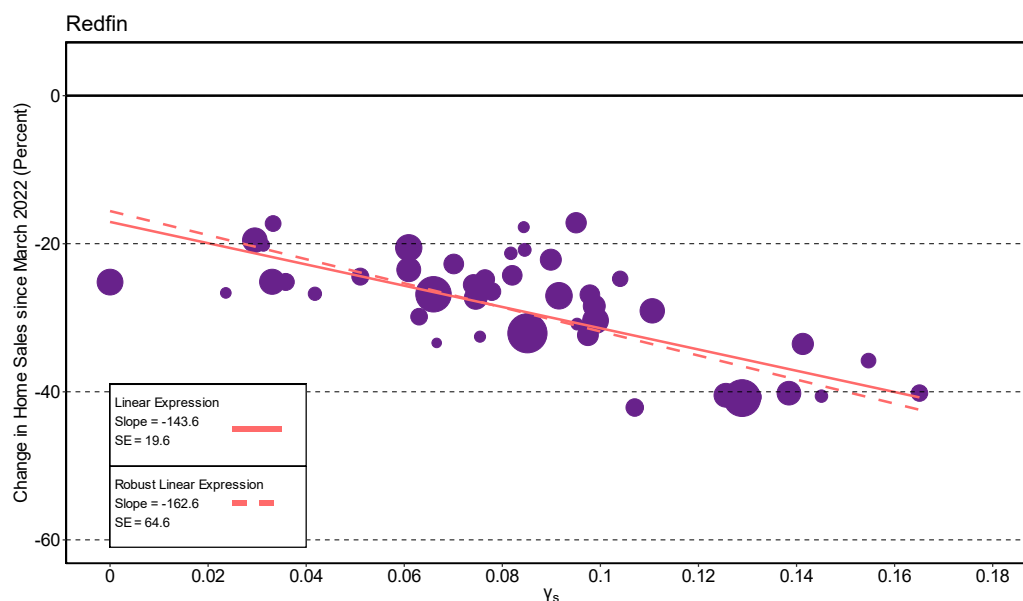


A. Additional Figures

Figure A.1: Change in Home Sales since March 2022
and State's γ_s



Source: Authors' calculations based on Redfin data and Home Mortgage Disclosure Act data

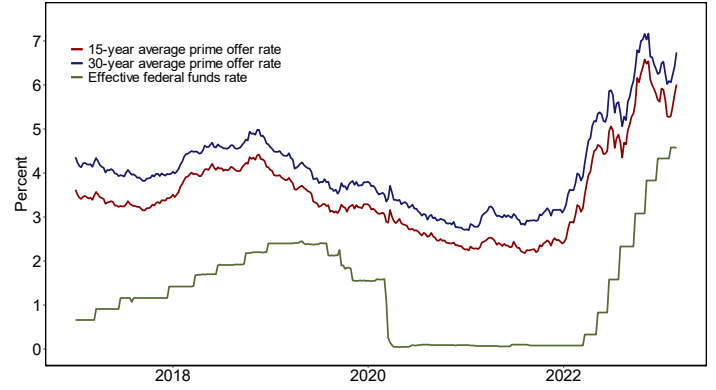
Note: The solid line shows the linear relationship between the change in home sales at the state level and γ_s . The dashed line presents the estimated linear relationship after accounting for outliers, following the procedure in Jann (2021). All calculations are derived starting from two-month average series.

B. Identifying Changes in a State's Financing Costs when Monetary Policy Tightens

Our goal is to estimate how much mortgage rates for identical loan and borrower characteristics increase in a specific state relative to the increase in a baseline state when the federal funds rate increases. We then use this variation across states as a proxy by assumption of how financing costs in a specific state change relative to the same change for a baseline state when the federal funds rate increases.

Since we are using Home Mortgage Disclosure Act (HMDA) data for 2021, we do not see changes to the federal funds rate during our sample period. However, the HMDA data provide a number for each loan of the “average prime offer rate” (APOR). This is the rate for the type of mortgage product for a “best-quality” 80 percent loan-to-value first-lien loan. The APOR does not vary at the state level. While small, we observe some time variation within our sample period in the average prime offer rate. As shown in Figure B.1 the average prime offer rates for 15- and 30-year mortgages co-move with the federal funds rate, even if their changes are not perfectly aligned and the average prime offer rates are more volatile. Based on this evidence, we will assume that changes in the APOR are equivalent to changes in the federal funds rate, and we use the variation in the average prime offer rates as a replacement for variation in the federal funds rate. Our estimates in this section then capture how mortgage rates for identical loan and borrower characteristics change at the state level when the national average prime offer rates change. Using our first assumption, we will interpret our estimates as the change in mortgage rates at the state level for identical loan and borrower characteristics when the federal funds rate increases.

Figure B.1: Average Prime Offer Rates (HMDA) and Effective Federal Funds Rate



Source: HMDA data and Federal Reserve Bank of New York

Within the complete 2021 HMDA data, we focus only on conventional first-lien loans and discard all observations in which the action taken does not correspond to loan origination. This leaves us with 43.4 percent of the original number of observations in the complete 2021 HMDA. We additionally discard all observations in which the purpose of the loan is not a home purchase, home improvement, refinance or cash-out refinance (1.4 percent of the remaining observations).

Our empirical specification is shown in Equation (1)

$$r = \beta_0 r^* + \sum_{s \in S} \alpha_s 1(s = \text{state}) + \sum_{s \in S} \gamma_s r^* 1(s = \text{state}) + \beta_1 LVratio + \beta_2 \ln(PV) + \beta_3 \ln(Inc) + \beta_4 \ln(LA) + \beta_5 LCosts + \beta_6 OCosts + \beta_7 Points + \beta_8 LCredits + \mathbf{X}_{tr} + \mathbf{FE} + e \quad (1)$$

where r is the interest rate of the loan, and r^* is the average prime offer rate associated with the loan. $s \in S$ represents each of the US states, and α_s captures state fixed effects. Similarly, $LVratio$ is

the loan-to-value ratio, $\ln(PV)$ is the natural logarithm of the property value, $\ln(Inc)$ is the natural logarithm of the applicant income, $\ln(LA)$ is the natural logarithm of the loan amount, $LCosts$ is the dollar amount in total loan costs divided by the loan amount, $OCosts$ is the dollar amount in loan origination costs divided by the loan amount, $Points$ is the dollar amount in points divided by the loan amount, and $LCredits$ is the dollar amount in lender credits divided by the loan amount. X_{tr} includes tract level controls.¹ FE includes several sets of loan and borrower fixed effects.²

Our coefficients of interest are γ_s , which are shown in Table B.1. They represent the elasticity of mortgage rates with respect to change in the average prime offer rate for each state relative to one of the states that works as the baseline.

The data from HMDA suffers primarily from three limitations. First, it does not provide the credit score of the applicant. The use of state fixed effects guarantees that our estimates would not be biased even if applicants have, on average, different scores across states and that difference affects their mortgage rates. However, if the average credit score varies differentially across states when the average prime offer rate increases, our coefficients of interest could be picking up this effect. However, this is not necessarily a major issue in our setting since we are interested in the differential effects of tighter monetary policy on borrowing costs across states regardless of whether the main source of these differences arises from the credit score of the applicants or some other state characteristics.

Second, the HMDA definition of discount points appears more restrictive than the definition from other sources. This could result in a lower share of loans in the HMDA with associated discount points, even if these borrowers are still paying a fee (that does not fall under the HMDA definition of discount points) to lower their interest rate. If the number of loans in which discount points are not correctly recorded changes differentially across states when rates increase, we could be picking up this measurement error in our coefficients of interest. However, when we compare HMDA data with data from Freddie Mac for the same year,³ we find that the share of mortgages that paid discount points in both samples is reasonably close and, if anything, appears slightly higher in the HMDA data. Freddie Mac reports that for a specific subset of mortgages, only 31 percent of purchases, 36 percent of refinances, and 47 percent of cash-out-refinances paid discount points.⁴ Using similar restrictions in the HMDA data, we find that 34 percent of purchases, 40 percent of refinances, and 53 percent of cash-out-refinances paid discount points.⁵ Therefore, these results suggest that despite the potentially more restrictive definition of discount points in the HMDA, the share of loans that paid discount points in the HMDA appears consistent with that reported in other sources and should not be a major concern in our analysis.

¹ Population, minority share, median family income, tract to MSA family income ratio, number of owner-occupied units, number of housing units, and the median age of the housing units.

² These fixed effects include: loan purpose (home purchase or refinance), purchaser type, loan term, whether the loan has an interest-only payment clause or has a balloon payment, credit score type, co-applicant, conforming loan, dwelling category, ethnicity, race, gender, age, and debt to income ratio of the applicant and whether there is a co-applicant.

³ <https://www.freddiemac.com/research/insight/20220425-trends-mortgage-refinancing-activity>

⁴ Mortgages for a home purchase or refinance of a single-family owner-occupied property with a fully amortizing 30-year fixed mortgage, for borrowers with conforming loans, and with credit scores 740 or above and a loan-to-value ratio between 75 and 80 (both inclusive).

⁵ We apply identical restrictions except for the category of credit score because we do not observe credit score information in HMDA. Given the strong positive correlation between income and credit score, in HMDA we restrict to loans in which the borrower's income is above the 50th percentile in our sample (102 thousand dollars).

Third, the data from the HMDA appear to under-record the lender credits in a given loan relative to other data sources such as OptBlue. This could be an issue if lender credits change differentially across states when rates increase. In that case, we could be picking up this measurement error in our coefficients of interest. To deal with this issue, our main specification adds as an additional control the total amount in loan costs, an amount which includes all fees paid by the borrower net of the lender or other third-party credits. The inclusion of this control should mitigate the potential issues arising from the potential under-recording of lender credits.

Finally, as additional robustness, we use two alternative data restrictions during the data cleaning process. The first one restricts the observations based on the loan purpose, focusing only on home purchases and refinances, while the second one makes no restrictions on the loan purpose. Regardless of the alternative, we still find almost identical results. The correlation of the state coefficients of the first alternative with our main state coefficients shown in Table B.1 is 0.960. In the case of the second alternative, the correlation of the state coefficients with our main state coefficients in Table B.1 is 0.998.

Table B.1: Estimated γ_s by State (s)

s	γ_s	s	γ_s	s	γ_s	s	γ_s
AK	0.067*** [0.009]	ID	0.155*** [0.005]	MT	0.110*** [0.007]	RI	0.095*** [0.006]
AL	0.076*** [0.004]	IL	0.092*** [0.003]	NC	0.061*** [0.003]	SC	0.074*** [0.003]
AR	0.091*** [0.005]	IN	0.090*** [0.003]	ND	0.094*** [0.008]	SD	0.151*** [0.008]
AZ	0.126*** [0.003]	KS	0.104*** [0.005]	NE	0.042*** [0.005]	TN	0.099*** [0.003]
CA	0.129*** [0.002]	KY	0.078*** [0.004]	NH	0.085*** [0.005]	TX	0.066*** [0.002]
CO	0.141*** [0.003]	LA	0.063*** [0.004]	NJ	0.075*** [0.003]	UT	0.165*** [0.004]
CT	0.036*** [0.004]	MA	0.070*** [0.003]	NM	0.084*** [0.006]	VA	0.111*** [0.003]
DC	0.110*** [0.008]	MD	0.097*** [0.003]	NV	0.107*** [0.004]	VT	0.024*** [0.008]
DE	0.075*** [0.006]	ME	0.082*** [0.006]	NY	0.000 [.]	WA	0.138*** [0.003]
FL	0.085*** [0.002]	MI	0.061*** [0.003]	OH	0.030*** [0.003]	WI	0.082*** [0.003]
GA	0.099*** [0.003]	MN	0.098*** [0.003]	OK	0.051*** [0.005]	WV	0.067*** [0.007]
HI	0.145*** [0.007]	MO	0.095*** [0.003]	OR	0.131*** [0.004]	WY	0.115*** [0.009]
IA	0.033*** [0.004]	MS	0.031*** [0.006]	PA	0.033*** [0.003]		

Source: Authors' calculations based on HMDA data

Note: Each coefficient γ_s on the table is estimated following Equation (1). It represents the increase in mortgage rates in the state relative to the increase in New York for identical borrower and loan characteristics when the average prime offer rate increases by 100 basis points.

C JOLTS Job Opening State Estimates

As discussed in the main text, we do not use JOLTS job opening (JO) estimates at the state level for our second strategy. The main reason is the small sample sizes (published by the Bureau of Labor Statistics (BLS) for September 2021 in its website.⁶) behind these estimates. Given the sample size limitations at the state level, the BLS uses a four-step model to estimate job openings for each state. The basic idea behind the model is to use JOLTS data when the sample size is sufficiently large and to use QCEW data, under strong assumptions, for those cases in which the sample size is not large enough to use JOLTS data. Since the QCEW data are available only with a 6- to 9-month lag, to provide current estimates at the state level for job openings, the BLS extrapolates the baseline estimates at the industry-state level using the changes at the industry-census region level observed in JOLTS.

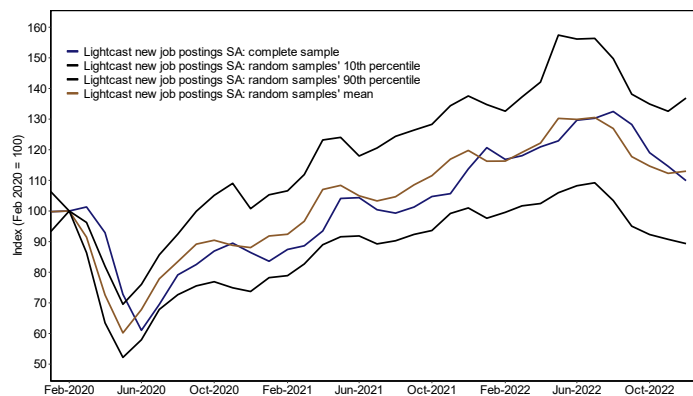
While we cannot backtrack the procedure followed by the BLS to construct the JOLTS state estimates, we can use the Lightcast microdata on online job postings to test whether using sample sizes at the state level of the size available for JOLTS still provides precise estimates of our main results in this *Economic Commentary*. To do this, we extract 100 random samples of firms such that in each sample the number of firms in each state matches the number of firms at the state level reported by JOLTS for September 2021 (the last month in which the BLS reports it).

Using these random samples, we calculate a national estimate of new online job postings (OJP) from Lightcast, equivalent to the one shown in Figure 1 in the main *Economic Commentary* text along with an estimate of the correlation shown in the left-hand panel of Figure 4 in the main *Economic Commentary* text (Figure 1 and Figure 4 in the main *Economic Commentary* text are calculated from our complete Lightcast sample).

As shown in Figure C.1, at the national level, we find few differences in the evolution of OJP over the last 3 years regardless of whether we use the complete Lightcast sample or a random sample of firms with the same sample size of JOLTS. The mean across the 100 different random samples (dashed blue line in Figure C.1) follows the estimate of the complete sample (solid blue line in Figure C.1) almost perfectly, and the 10th and 90th percentiles (dashed black lines in Figure C.1) are relatively narrow.

However, the situation is different when trying to replicate the results at the state level. As shown in Figure 4 in the main *Economic Commentary* text, we estimate a negative and significant correlation between the change in vacancies at the state level and the state's γ_s in our complete Lightcast sample (Point estimate=-85.3, SE=37.0). But the mean estimate of this correlation from

Figure C.1: Lightcast OJP: 2020–2022.
Complete Sample versus Random Sample of JOLTS size



Note: All series are two-month moving averages.

⁶ See https://www.bls.gov/jlt/jlt_statedata_methodology.htm#Sample.

our 100 random samples is slightly positive (28.9), and the standard deviation of the distribution of the estimates of this correlation is very large (419.8).

These results suggest that a random sample of Lightcast's data of the same size used in JOLTS can provide precise estimates of the evolution of OJP at the national level, but it is not large enough to reliably estimate the changes observed over the last few months at the state level. In light of this evidence, we do not use JOLTS estimates at the state level for our second empirical strategy.