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# House Prices, Debt Burdens, and the Heterogeneous Effects of Mortgage Rate Shocks

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## Why These Findings Are Important

Mortgage rates are influenced by financial markets and monetary policy, and these have a relationship with home prices. Typically, as mortgage rates rise, home prices fall, and when rates fall, home prices rise. Residential real estate is an important asset class to consider when assessing the stability of the financial system due to its size and interconnectedness across households, banks, and nonbank financial institutions.

## Key Findings

1. **High borrower debt service-to-income (DTI) ratios and tight DTI underwriting limits amplify the effects of mortgage rate shocks on house prices**

2. **House price sensitivity to mortgage rates is near a 21st century high.**

## How the Authors Reached These Findings

This research uses cutting edge methods in empirical macroeconomics, including state-dependent local projections with instrumental variables. Models are estimated using city-level house prices, allowing the effect of mortgage rates to vary by a city's recent history of high-DTI mortgage borrowers. Mortgage rate shocks are identified using industry professionals' forecast errors and monetary policy surprises.

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**Abstract**

We examine the heterogeneous effects of mortgage interest rate shocks on house prices in a monthly panel of U.S. cities. Mortgage interest rate shocks, identified using Blue Chip forecast errors and monetary policy surprises, affect house prices more in cities where more borrowers have high debt burdens. This is consistent with a model with both price frictions and credit constraints. Responsiveness to interest rate shocks thus varies by location and time period, and is related to both borrower characteristics and underwriting rules. This has important implications for understanding monetary policy transmission, systemic risk, and the role of household finances in the macroeconomy.

**Keywords:** Asset Pricing · Household Finance · House Price Bubbles

**JEL Classification: G 21, G 51, E 43, R 30, C23.**

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# 1 Introduction

Widespread negative housing equity is an important determinant of systemic risk within the housing finance system. While it is known that higher mortgage rates put negative pressure on house prices and current equity, there is little research on the financial factors that could amplify such effects. Due to the important role of housing and mortgage assets on the balance sheets of households, banks, government-sponsored enterprises, and other investors, it is useful to understand the conditions under which house prices might be most sensitive to changing mortgage rates, especially when they are rising and could result in negative equity.

A stylized fact of housing asset price dynamics is that they can vary widely across space and time, and departures of prices from fundamentals can be sustained for years (Muellbauer and Murphy, 1997; Gallin, 2008; Mian and Sufi, 2009; Duca et al., 2010). A substantial body of research explores the rich variation in dynamics observed in the data (McQuinn and O'Reilly, 2008; Holly et al., 2010; Oikarinen et al., 2018; Johnson, 2020). A subset of this research focuses on the state-dependent effects of mortgage rates. This line of inquiry has almost exclusively focused on the elasticity of housing supply, finding that supply-elastic locations offer more muted price responses to interest rate shocks (Füss and Zietz, 2016; Aastveit and Anundsen, 2022; Gorea et al., 2022; Xie, 2024; Li et al., 2024).

We do three things in this paper. First, we present the stylized fact that high mortgage borrower debt service-to-income (DTI) ratios and tight DTI underwriting policy limits amplify the effects of mortgage rate shocks, identified using forecast errors and monetary policy surprises, on local house prices. Next, we explain this stylized fact using a simple model of a local housing market with heterogeneous preferences and borrowing constraints. The key insight is that the own-price elasticity of demand for housing is higher for payment-constrained households compared to unconstrained households. Thus, the response of house prices to mortgage rate shocks is more extreme in areas with a high fraction of constrained borrowers. More generally, due to risk layering in underwriting, rising mortgage rates have a second-order effect of higher rates through higher DTIs, pushing borrower payment burdens up further and reducing demand. Related predictions have appeared in forms within Kaplan et al. (2018) and Greenwald (2018). However, for our third and final contribution, we rigorously test these predictions and estimate empirical magnitudes. Importantly, our empirical results both affirm and encompass previous models that only considered the elasticity of housing supply, including Aastveit and Anundsen (2022) and Xie (2024).

To motivate our empirical analysis, we develop a simple model that shows the short-run effect of mortgage rate shocks on house prices depends on the own-price elasticity of demand for housing. In the model, we generate elasticity differences using DTI-based credit constraints. In response to an interest rate shock, demand falls more for constrained borrowers than unconstrained borrowers; the aggregate price effect in a location then depends on the share of constrained borrowers.[1]

In our model, borrowers are either constrained or unconstrained by strict mortgage payment limits, but in practice, borrowers face increasing rate sensitivity in a continuous manner as monthly payment burdens rise. This occurs due to the convex relation between default and primary credit risk factors, also called "risk layering": marginal DTI increases are associated with higher mortgage rates across the DTI distribution, and DTI-based loan application rejections in a city are positively associated with high observed DTIs for originated mortgages (Anenberg et al., 2019; Davis et al., 2023). This implies mortgage rate effects on house prices increase in magnitude with the share of households facing high mortgage payment burdens, not just those strictly bound by constraints.

Empirically, we estimate the effects of mortgage interest rate shocks on house prices in a state-dependent local projections framework following Jordà (2005), Stock and Watson (2018), and Cloyne et al. (2023). We identify mortgage rate shocks using two common approaches in the literature: 1-month-ahead mortgage rate forecast errors, as estimated by Blue Chip Financial Forecasters (BCFF); and alternative measures of high-frequency surprises in longer-term interest rates following Federal Reserve Open Market Committee meeting announcements, as measured by Gürkaynak et al. (2005), Swanson (2021), and Bauer and Swanson (2023b). Our state variable of interest is the local fraction of new mortgage originations with high ($> 43$) DTIs. While DTIs are endogenous with respect to house prices

[1] Constrained borrowers have unit elastic demand because DTI constraints are essentially expenditure constraints when housing is debt-financed, so demand falls at the same rate as the effective price increases. Greenwald (2018) formalizes many of these concepts into a structural model of a macroeconomy that models the effects of such DTI (also called payment-to-income or PTI) constraints on the transmission of interest rate shocks. This model includes DTI constraints, loan-to-value (LTV) constraints, and durable housing in addition to housing, goods, and debt markets. It shows how DTI constraints can generate important monetary policy transmission effects. In response to a change in the inflation target, an economy with a binding DTI constraint faces larger changes to mortgage debt and house prices than an economy without DTI constraints. Similar to Kaplan et al. (2018), Greenwald (2018) finds LTV constraints, on their own, do little to affect house prices or propagation of shocks. Beyond Kaplan et al. (2018) and Greenwald (2018), there is little formal analysis of the demand-side interactions of monetary policy or interest rate shocks on house prices involving debt burdens and constraints.

and mortgage rates, we identify the state-dependent effect of mortgage rate shocks interacted with DTI variables and control for changes in the state variable following the approach by Alloza et al. (2023). Identification of the state-dependent effect is accomplished by including leads of the endogenous state variable, in our case, DTI.

Using monthly data from 253 U.S. cities between 2000 and 2022, we show that the city-level dynamic response of house prices to mortgage rate shocks is augmented by three state variables: (1) the share of borrowers with high DTIs, (2) national DTI underwriting policy limits, and (3) the elasticity of housing supply. The share of borrowers with high DTIs amplifies the effects of mortgage rate shocks on house prices, with a partial effect of the $DTI > 43$ share on the three-year semi-elasticity of house prices with respect to mortgage rates of -1.25. Additionally, the partial effect of a one percentage point decrease in the DTI underwriting limit is -1.24. Our conclusion is that debt burdens and policies governing DTI underwriting limits have important implications for the transmission of mortgage interest rate shocks to house prices both across cities and within the same city over time.

However, partial effects can be difficult to interpret due to correlations among the explanatory variables. When we use actual values for cities in the United States, we find that the total 3-year semi-elasticity of house prices with respect to mortgage rates rises from about 4% in the early 2000s to approximately 28% in 2022 due to changes in DTI-based underwriting rules and the share of borrowers with extreme DTIs ($> 43$).[2] The cross-city standard deviation in the semi-elasticity varies as well, ranging between 4% and 8% depending on city-level extreme DTI shares and the elasticity of housing supply.

Models with state-dependent effects, but without DTI interactions, such as those found in Aastveit and Anundsen (2022), show large effects of the elasticity of housing supply on price dynamics. We replicate and confirm both this result and the use of the Saiz (2010) supply elasticity measure in explaining panel house price dynamics. However, we also observe that the supply elasticity and the share of high-DTI borrowers is highly correlated, and show that omission of the DTI interaction results in omitted variable bias and mis-attribution of some of the causal effect from borrower indebtedness to the supply elasticity. When we control for DTI variables, the housing supply elasticity effect falls by about 40%. Our interpretation of

[2]A "semi-elasticity" is a *percentage point* change in one variable's effect on a *percent* change in another variable. In this context, the house price semi-elasticity with respect to the mortgage rate is the percent change in house prices due to a one percentage point change in mortgage rates.

this result is that higher (lower) supply elasticities affect house price dynamics indirectly by lowering (increasing) the house price level and increasing (decreasing) the share of high-DTI borrowers, as opposed to directly via new construction. This makes some intuitive sense, as housing may be constructed too slowly to substantially cushion the short-run effects of demand shocks on prices (Oh et al., 2024).[3] On the other hand, mortgage rate shocks affect loan terms for all prospective borrowers who do not yet have rate locks, altering borrower payment burdens with a lag of 1 to 2 months.

In addition to our results concerning panel house price dynamics, there are also important implications of our work for understanding interest-rate pass-through to the macroeconomy. This is a broad literature, but it can be divided roughly into three relevant lines of inquiry. First, there is the effect of monetary policy on national house prices. Empirically, while work using data prior to 2007 has shown mixed results on the effects of consumer debt on monetary policy transmission to house prices (e.g. Alpanda and Zubairy, 2019), Paul (2020) shows semi-elasticities rose post-2008 using monetary policy shocks and VARs with time-varying parameters. We delve into the mechanism and show that this is, in part, due to changes to underwriting limits and borrower indebtedness. Conceptually, our research is perhaps most related to Greenwald (2018), who models mortgage interest rates and housing within a DSGE model of the U.S. economy, finding that payment-to-income ratio policy limits amplify the propagation of interest rate shocks. The present research builds on this concept, layering onto this model heterogenous supply responses across cities and empirically testing some of its key predictions. Our findings suggest that monetary policy transmits to the real economy through house prices in a manner that depends on current levels of household debt. Because mortgage underwriting, along with household debt, affects the propagation of interest rate shocks, housing finance regulators, other regulators in the household finance space, and monetary authorities may wish to coordinate to internalize policy spillovers, such as the United States has done with its Financial Stability Oversight Council in its Dodd-Frank era.

The second relevant line of research is the housing market channel of monetary policy transmission. Di Maggio et al. (2017) show declines in mortgage interest rates at ARM reset points increase consumption of consumer durables, including automobiles. Beraja et al. (2019) show

[3] According to the Census Bureau information on residential construction, in 2022, average permitting time was 1.4 months for single-family units and 2.8 months for 2+ unit buildings. After permitting, average construction time was 8.3 months for single-family units and 17.0 months for 2+ unit buildings.

the Federal Reserve's quantitative easing policies induced differential rates of refinancing activity that are associated with a region's accumulated home equity, and this had effects on regional aggregate spending. Cloyne et al. (2020) show that in the UK, households with high levels of mortgage debt respond to interest rate changes with changing consumption patterns. Recently, Ringo (2024) presents evidence that inframarginal borrowers, who might not respond directly to mortgage rate shocks on the extensive margin of mortgage choice, cause substantial pass through of mortgage rates to mortgage debt and consumption.

The final line of literature considers the effects of borrower indebtedness more generally, and how this state variable affects monetary policy transmission to consumption. Because DTIs consider all household debts, including auto loans, credit card debt, and student loan debt, there is a direct effect of all debt classes on interest rate pass-through to the housing market and beyond. Mian et al. (2013) shows wealth shocks brought about by house price declines led to reduced consumption in the Great Recession, and Iacoviello (2005) argues that monetary policy affects homeowners' balance sheets and can affect consumption through a housing wealth channel. Kim and Lim (2020) and Cumming and Hubert (2023) find that high household debt levels amplify monetary policy transmission to consumption. Our research offers complementary evidence in line with these findings. Overall, our research points to the need for heterogeneous agent models of the macroeconomy (e.g., Mitman, 2016; Debortoli and Galí, 2018; Kaplan et al., 2018) to understand how some highly-indebted agents may have an out-sized effect on market price dynamics and other behaviors that are relevant in aggregate.

## 2 Conceptual Framework

Housing asset prices may respond differently to changes in mortgage interest rates for a variety of reasons. Much of the empirical literature has focused on the responsiveness of supply, which absorbs some of the shock rather than demand. This literature uses measures of the elasticity of housing supply and land use regulations to explain heterogeneous price dynamics; see, e.g., Green et al. (2005), Aastveit and Anundsen (2022), Xie (2024), and others. We consider an alternative explanation: prospective borrowers who would take on mortgages with high debt service-to-income ratios (DTI) are more sensitive to changes in rates than those with low prospective DTIs. This is because borrowers with high DTIs face increasing funding costs due to credit risk layering and higher propensity of facing strict DTI underwriting constraints. Such borrowers cannot easily adjust their monthly mortgage payments (i.e. expenditure) in response to a change in interest rates as would households with low DTIs. The high-DTI share of borrowers in an area thus amplifies the demand effects of mortgage rate shocks, with resulting effects on prices.

## 2.1 Model

To formalize these concepts, we develop a simple model of a housing market that is built up from demand curves for individual households. The effect of a mortgage rate change on housing demand depends on the own-price elasticity of demand for housing. The only source of variation in the elasticity of demand is the share of borrowers in a market who are bound by DTI constraints; we do not consider risk layering, as key predictions are generated without this additional complexity.

The market is fully segmented and considers only owner-occupiers; as such, the user cost of homeownership is the relevant flow price (see e.g. Poterba, 1984; Himmelberg et al., 2005; Glaeser and Gyourko, 2007; Loewenstein and Willen, 2023). Households are identical except for housing preferences, which exist on a continuum. Housing supply is fixed and both households and housing units are infinitely lived. Housing is fully financed using non-amortizing, interest-only fixed-rate mortgages. There is a single mortgage rate on offer; there is no default in this model. The decision facing households is how much housing to consume, subject to a DTI constraint. In aggregate, frictions exist, preventing prices from changing instantaneously, with the appreciation rate assumed proportional to the demand imbalance.

Suppose a user cost function, where the imputed rental price of housing $R$ is equal to the asset price $P$ multiplied by the difference between the mortgage rate $r$ and the appreciation rate $g$, with $r > g$ assumed

$$R = P(r - g). \tag{1}$$

Then, assume a DTI underwriting maximum $\theta$, where $h$ is the quantity of housing consumed, and $Y$ is the household's income

$$\theta \geq \frac{hrP}{Y}. \tag{2}$$

As we will show, without market clearing, $r$ affects housing demand in a manner related to the share of borrowers, $\lambda$, bound by payment constraints. A necessary condition for this effect is an own-price elasticity of demand for housing, $\sigma$, that is between 0 and -1. Albouy et al. (2016) show in a meta-analysis that this parameter usually falls between -0.5 and -0.9.

An individual's housing preference $z$ exists on a continuum between 0 and 1. Then, assume an individual demand curve with an income elasticity of demand of 1 and an own-price elasticity of housing demand $\sigma < 0$

$$\begin{aligned} h &= zYR^{\sigma} \\ &= zY(r-g)^{\sigma}P^{\sigma}. \end{aligned} \tag{3}$$

Optimal household-level housing consumption conditional on the price, interest rate, and income, subject to the DTI constraint in equation 2, is then

$$h^* = \min\{zY(r-g)^{\sigma}P^{\sigma}, \theta Y(rP)^{(-1)}\}. \tag{4}$$

There is a cutoff value of housing preference where households become constrained, $\tilde{z} = \theta r^{-1}(r-g)^{-\sigma}P^{(-1-\sigma)}$, which is found by taking the two arguments in (4), setting them equal, and solving for $z$. Households with low housing preference are unconstrained and demand is unaffected by $\theta$, whereas households at or above the constraint are affected by $\theta$. We can now define the share of borrowers bound by monthly payment constraint as $\lambda = 1 - \tilde{z}$. This share is positively related to the mortgage rate, the housing asset price, expected appreciation, and the DTI constraint.

Aggregate housing demand $H^*$ is found by integrating over $z$, which involves integrating over the values of $z$ when $\theta$ is binding and when it is not:

$$\begin{aligned} H^* &= \int_0^{\tilde{z}} zY(r-g)^{\sigma}P^{\sigma}dz + \int_{\tilde{z}}^1 \theta Y(rP)^{-1}dz \\ &= \underbrace{\frac{1}{2}Y(r-g)^{\sigma}P^{\sigma}}_{\text{All Borrower Channel}} - \underbrace{\frac{\lambda^2}{2}Y(r-g)^{\sigma}P^{\sigma}}_{\text{Constrained Borrower Channel}}. \end{aligned} \tag{5}$$

The first integral covers housing demand from unconstrained borrowers, and the second integral covers demand from those who are constrained. Evaluating the integrals and substituting for $\tilde{z}$, we arrive at the second expression (see Appendix B for derivations).

The first term captures the negative effect of $r$ on $H^*$ which is common to both constrained and unconstrained borrowers. The second term considers the effects on constrained borrowers. This second term captures two effects of interest rates: a negative direct effect on demand, and a positive indirect effect on the share of constrained households (recall $\lambda = 1 - \tilde{z} = 1 - \theta r^{-1}(r-g)^{-\sigma}P^{-1-\sigma}$) which pushes demand down further. Combined, the effect of interest rates on housing demand is negative and decreasing in $\theta$. Taking the derivative of (5) with respect to $r$ confirms that $\lambda$ is negatively related to housing demand

$$\frac{dH^*}{dr} = \underset{(-)}{\frac{\partial H^*}{\partial r}} + \underset{(-)}{\frac{\partial H^*}{\partial \lambda}} \underset{(+)}{\frac{d\lambda}{dr}} < 0. \tag{6}$$

But $\lambda$ itself is determined by parameters, so it is useful to consider the effect of changes to underwriting, $\theta$, on the derivative in equation 6. Relaxing payment constraints via an increase in $\theta$ reduces the negative effect of interest rates on demand

$$\frac{d^2H^*}{drd\theta} = \underset{(+)}{\frac{\partial^2 H^*}{\partial r \partial \theta}} + \underset{(+)}{\frac{\partial^2 H^*}{\partial \lambda \partial \theta}} \underset{(+)}{\frac{d^2\lambda}{drd\theta}} > 0. \tag{7}$$

In a market with frictions, in the short-run, the housing market does not clear, i.e. there are vacancies. To return to equilibrium, house prices change in a manner proportional to the deviation in housing demand relative to the housing stock (e.g., $\Delta P = \alpha(\bar{H} - H^*)$, where $\alpha < 0$). We interpret the preceding analysis of effects of interest rates on housing demand as proportional to short-run effects of interest rates on changes in housing asset prices.

## 2.2 Model wrap-up and discussion

So what does the model tell us? Simply put, borrowers who reach their maximum debt levels cannot take on additional debt. For owner-occupied housing that is mortgage-financed, this means that borrowers who have reached such debt service constraints cannot cushion an increase in interest rates by increasing expenditures. Rather, constrained households must reduce consumption by more than would be optimal in an environment without such binding DTI constraints. This occurs because demand for housing is inelastic. When a housing market consists of a large fraction of such constrained borrowers, interest rates reduce housing demand by more than in an area with few such borrowers. This effect is symmetric because borrowers who are currently bound by a DTI constraint may increase expenditures by more than the unconstrained elasticity would imply were interest rates to fall. This model does not consider alternative means of adjustment, for instance, transitions from owning to renting, or the role of investors who may be less credit-constrained. But assuming some frictions that prevent these other possibilities from completely absorbing this debt constraint effect, the model's predictions should be maintained.

A common claim in this literature is that DTIs cannot affect house prices very much because so few borrowers are actually bound by constraints (see Kaplan et al., 2018). We challenge this argument on two grounds: First, Greenwald (2018) shows how DTI constraints, when paired with LTV constraints, serve to produce a major amplification of the effects of interest rates on house prices. The reason is termed by Greenwald (2018) as “constraint switching”, where a borrower that is subject to DTI constraints chooses to change their downpayment in response to changing collateral values. This produces a second-order effect on house prices that is larger than the initial effect on maximum loan amounts. Second, DTI constraints need not be binding for high DTIs to increase borrowing costs. Davis et al. (2023) show how the layering of risk attributes such as LTV, DTI, and credit scores, can increase mortgage default rates, meaning that marginal credit risk can increase substantially at even moderate DTIs. Anenberg et al. (2019) then show how such risk layering can cause marginal DTI increases, resulting in higher mortgage rates for borrowers well below DTI constraints.[4] Accordingly, it is likely that the elasticity of demand increases in magnitude as a borrower *approaches* the DTI limit, not just those at the limit. The share of borrowers *nearing* payment constraints may serve as a better proxy for the elasticity of demand and augment effects of mortgage rate shocks on house prices, than a measure of borrowers strictly bound.

# 3 Data and Descriptive Statistics

Testing the conjectures in the previous section requires a panel dataset on house price appreciation and mortgage loan characteristics in a large number of cities. We use Freddie Mac’s house price index for house prices because it is high-frequency (monthly) and geographically granular (cities). This is merged with public data on borrower and loan characteristics from Fannie Mae’s single-family loan-level dataset. Our final balanced panel dataset includes monthly values for 383 U.S. core-based statistical areas (CBSAs) between January 2000 and August 2022. These series are supplemented with publicly available measures of interest rates, monetary policy shocks, public underwriting criteria, and other macroeconomic indicators at the national level, and land use regulations and other cross-sectional attributes at

[4]We verify this relation in binned scatter plots in figures 2 and A.3. In every year and for nearly every DTI, a DTI increase is associated with a higher mortgage rate, conditional on LTV, credit score, and first-time homebuyer.

the CBSA level.[5] After these various merges are complete, we are left with 253 CBSAs.

## 3.1 House prices

We use Freddie Mac's repeat-sales house price index due to its high frequency, city granularity, and its treatment of adjusting refinance appraisals for possible bias.[6] Common stylized facts for U.S. house price indices are readily found in Oikarinen et al. (2018) and Bogin et al. (2019). House prices tend to evolve in long (8-12 year) cycles but with considerable heterogeneity both in length and in depth across cities. Figure 1 panel (a) shows the 5th, 50th, and 95th percentile annualized appreciation rates across cities within a given month. For most years since 2000, median appreciation has ranged between 0 and 10%. The two exceptions are the 2006-2012 financial crisis/Great Recession period, and the 2020-2022 COVID-19 boom period. The run-up in prices in the 2002-2006 period was unevenly distributed across geographies, with the 5th percentile barely seeing any gains. In contrast, during the COVID-19 period, even the 5th percentile saw appreciation rates around 10%. The spread between the 5th and 95th percentile appreciation rates is anywhere between 10 and 30 percentage points, depending on the month. Combined, these facts suggest substantial heterogeneity in growth rates and dynamics across cities.

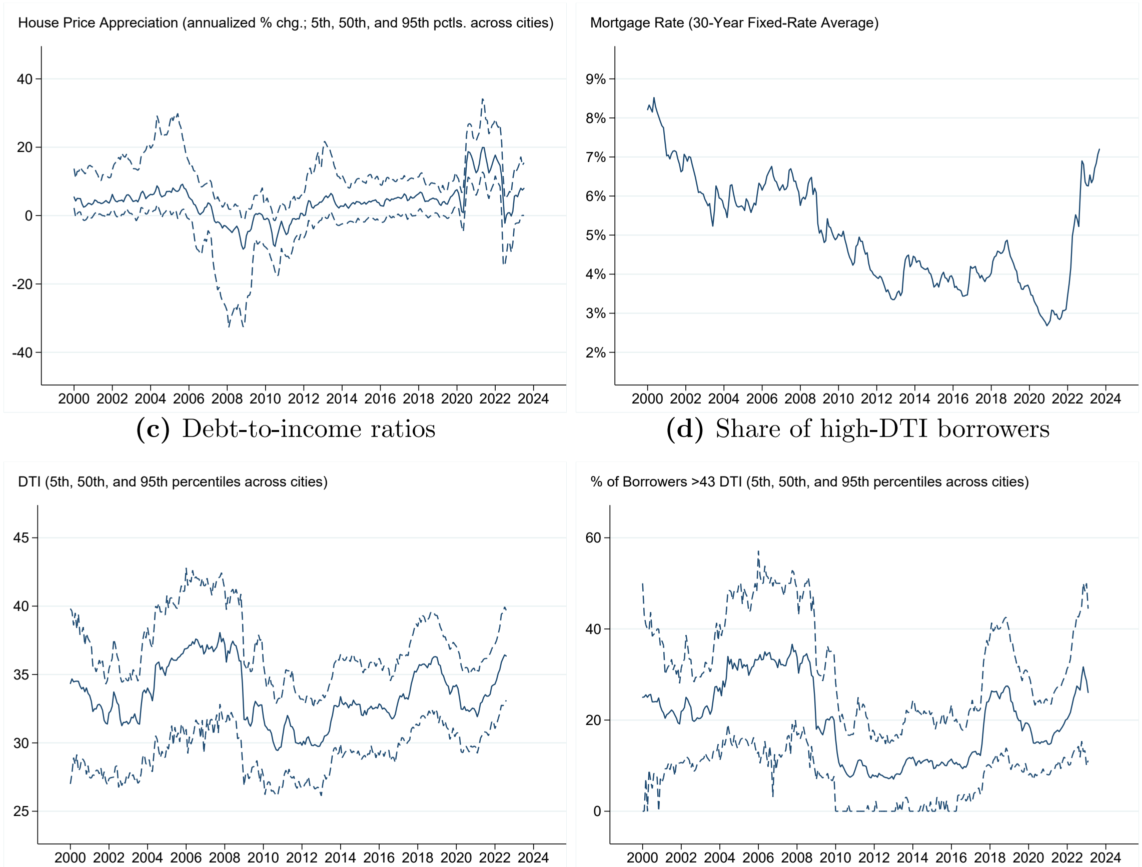
[5] Throughout, all variables are nominal, though economists are divided on the use of real versus nominal house prices in time series contexts. For instance, while McQuinn and O'Reilly (2008); Saiz (2010), and others use nominal prices, Gallin (2006); Holly et al. (2010), and others use real. For mortgage borrowers, mortgage-backed security investors, and financial regulators, the nominal house price determines the equity of a home and collateral for a mortgage. Additionally, inflation dynamics with house prices may also be different than inflation dynamics with wages and other house price determinants, especially in the short-run. Accordingly, all variables are modeled as nominal.

[6] This database can be found at the following static URL: `https://www.freddiemac.com/research/indices/house-price-index`. The index used is the seasonally-adjusted series. See `https://www.freddiemac.com/fmac-resources/research/pdf/FMHPI.pdf`. A "city" is a Core-Based Statistical Area (CBSA) with 2020 definitions.

**Figure 1:** Time Series

**(a)** House Prices **(b)** Mortgage Rates

**(c)** Debt-to-income ratios **(d)** Share of high-DTI borrowers




Sources: Freddie Mac; Fannie Mae; Authors' analysis.

## 3.2 Borrower, loan, and underwriting statistics

Our conceptual framework highlights the need for a measure of mortgage borrower payment burdens. The standard measure of payment burden used in mortgage underwriting is the back-end "debt-to-income" ratio, or DTI. This measure is calculated by taking all monthly debt service payments and housing expenses and dividing by the household's income. The numerator includes the payment on the new mortgage, property taxes, homeowners association fees, homeowners insurance, and all other debt, including student loans, auto loans, and credit card debt.[7] The prospective DTI for a new mortgage is used in loan underwriting to determine the offered mortgage interest rate or if a loan will be offered at all. As the prospective DTI rises, the loan faces a higher offered mortgage rate and runs the risk of

[7]Note DTI measures borrower payment burdens, not indebtedness. For example, a \$100,000 mortgage with a 10% interest rate has a larger effect on DTI than a \$200,000 mortgage with a 3% interest rate.

being rejected due to an accumulation of expected default risk or breaching underwriting rules regarding DTI maximums.

Measuring borrower payment burdens is a difficult task because issued mortgages are subject to a variety of selection factors, and thus, are sampled from the population non-randomly. Furthermore, before 2008 income reporting was not held to a high standard and was thus often inaccurate.[8] Our preferred approach is to use newly-originated DTIs, as is standard in the literature, despite the potential measurement issues (e.g. Greenwald, 2018; Adelino et al., 2018; Davis et al., 2023). We create a variable representing extreme borrower payment burden, defined as any loan with a back-end DTI greater than 43, which we abbreviate to "DTI43". We take the simple average of all new originations in a particular city-month to construct $DTI43$ shares, and use this measure throughout as an easy-to-understand, parsimonious proxy for cross-sectional variation in the elasticity of demand for housing.

We use public data on single-family mortgages from Fannie Mae to construct our measures, following Greenwald (2018).[9] We focus on the Enterprise (Fannie Mae and Freddie Mac) segment because it occupies the middle 35% to 50% of the U.S. purchase-money mortgage market share over our sample period (Davis et al., 2023).[10] Our dataset covers nearly all loans purchased or securitized by Fannie Mae between 2000 and August 2022, excluding Home Affordable Refinance Program (HARP) loans and loans in pre-Great Recession subprime or Alt-A securities. From 2000 through 2008, Fannie Mae was considered to have more lax underwriting of the two Enterprises (Johnson, 2020), after which they and Freddie Mac harmonized much of their policies. Therefore, we treat Fannie Mae as the frontier of credit access from 2000 through the end of our sample for Enterprise underwriting.[11]

Figure 1 panel (c) shows the average DTIs at the 5th, 50th, and 95th percentile cities for each

[8] Some of these selection factors include preferring to rent or own, then conditional on intending to own, qualifying for a mortgage, then conditional on qualifying for a mortgage, sorting into the ideal loan contract given the menu of loan options currently available along with borrower expectations. See e.g. Brueckner (2000).

[9] The data used is Fannie Mae's public Fannie Mae Single-Family Loan Performance Dataset, found at `https://capitalmarkets.fanniemae.com/credit-risk-transfer/single-family-credit-risk-transfer/fannie-mae-single-family-loan-performance-data`.

[10] Our results are robust to measures calculated using both Fannie Mae and Freddie Mac together, and the mortgage market as a whole. We use the National Mortgage Database® to create these supplemental measures. See appendix.

[11] Our estimates are robust to the use of alternative DTI measures, including nationally representative samples in the National Mortgage Database.

month, and panel (d) shows DTI43s; for maps, see appendix figure A.2. As with house prices, there is a large spread in the 5th to the 95th percentile average DTIs of about 10 percentage points. The median value starts at about 35% in 2000, dips to about 32 in 2002-2004, and rises to 38 in 2006-2008 before collapsing to about 30 for the Great Recession period. From there, it recovered to about 33 in 2014 through 2018, when it increased further to about 36 in 2019. DTIs started to fall just before COVID-19, hitting a minimum of 33 before rising back to 36 alongside the increase in mortgage interest rates. The DTI43 share tracks average DTI very closely, with the exception of it falling more in relative terms between 2010 and 2018.

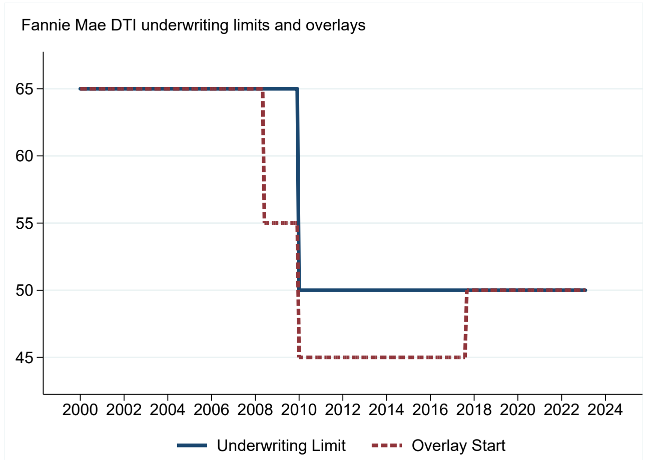
Why did DTIs fluctuate so much over the sample? A key factor was that DTI-based underwriting guidelines for mortgages changed substantially. Figure 2 shows various measures of underwriting limits and payment burden measures, with panel (a) showing strict and known eligibility overlay limits as reported by FHFA-OIG (2019) and public Desktop Underwriter software update notifications from Fannie Mae.[12] Panel (b) shows that originated mortgage rates rise with DTI, indicating that risk layering in underwriting contributes to higher payment burdens as DTIs rise, even at moderate levels. Panel (c) shows that $DTI43$ is highly correlated with rejected loan applications using Home Mortgage Disclosure Act (HMDA) data; at the city-year level between 2010 and 2022, a 10 percentage point increase in the share of new originations with DTIs greater than 43 in the Fannie Mae file is associated with a market-wide 5 percentage point higher loan rejection share due to too high DTI.[13]

[12]See appendix figure A.4 for annual DTI distributions, limits, and overlays. For example, the eligibility overlay required any loan with a DTI greater than 45 to be rejected if its LTV was greater than 80 or the borrower had fewer than 12 months of reserves, even if the loan were otherwise approved based on its calculated risk. This was eliminated in the updating of Desktop Underwriter version 10.0 to 10.1 in July 2017. See `https://capitalmarkets.fanniemae.com/media/6781/display` for more information.

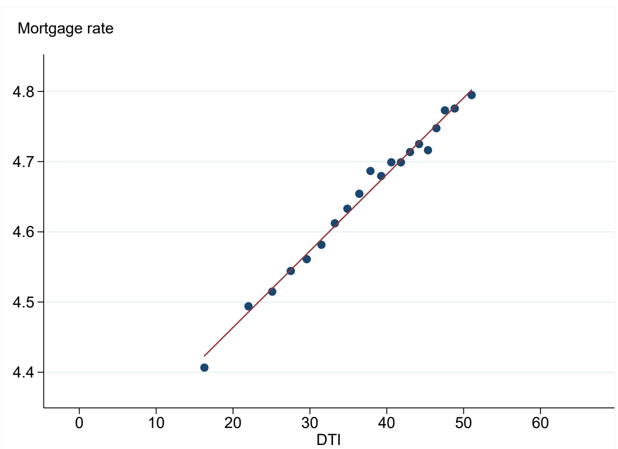
[13]The Consumer Financial Protection Bureau noted in its 2020 annual report that "The DTI ratio was overwhelmingly the most common reason for denial of home-purchase applications" (`https://files.consumerfinance.gov/f/documents/cfpb_2019-mortgage-market-activity-trends_report.pdf`).

**Figure 2:** Mortgage underwriting and DTIs

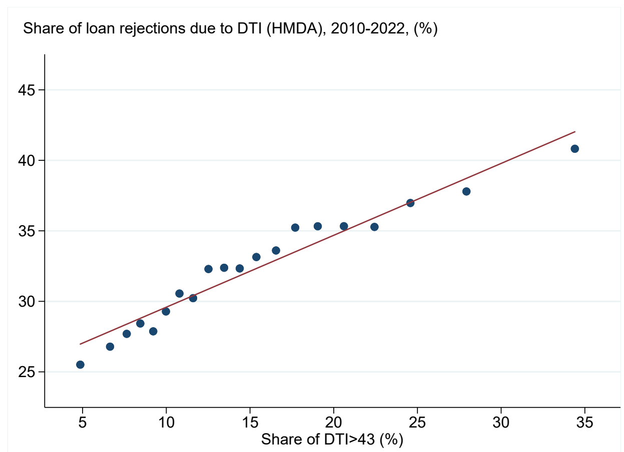
**(a)** DTI-based underwriting limits and overlays




**(b)** Origination mortgage rates and DTIs (2022)




**(c)** Rejected loans and extreme DTI originations




Notes: The scatter plots in (b) and (c) are calculated across 253 CBSAs using the "binscatter" command in STATA (e.g., Chetty et al., 2014) using the function written by Jessica Laird and available at `https://michaelstepner.com/binscatter`. The data include all owner-occupier, first-lien, purchase-money mortgages in the respective dataset. Each point represents a 5% sample bin. The plot in (b) is based on loan origination-level data, and is conditional on 8 bins of LTV, 8 bins of credit score, and a first-time homebuyer dummy. The plot in (c) is based on CBSA-year data with HMDA loan application count weights with no controls.

Sources: Federal Housing Finance Agency; Fannie Mae; Consumer Financial Protection Bureau; Authors' analysis.

## 3.3 Mortgage interest rates and instruments

We use the Freddie Mac 30-year fixed-rate average mortgage rate for the United States. This series is weekly in its raw state and is aggregated to monthly based on the within-period average. Figure 1 panel (b) shows mortgage rates declined steadily between 2000 and 2021 from about 8% to just under 3% for a 30-year fixed rate mortgage. Then, in response to the Federal Reserve's tightening monetary policy and changes in mortgage-backed security holdings, mortgage rates spiked to 7% in 2022.

To identify mortgage rate shocks, we use 1-month-ahead consensus forecast errors using monthly forecasts of the 30-year fixed-rate mortgage from the Survey of Blue Chip Financial Forecasters (BCFF). The BCFF survey is typically conducted between the 20th and 29th day of each month and consists of forecasts of interest rates from around 50 professional forecasters predominantly at financial institutions. Panel (b) in figure 3 plots the resulting forecast errors and illustrates its high correlation with changes in mortgage rates.

The BCFF forecast errors may not be completely exogenous. For example, Sherlund (2020) shows that most changes to longer-term interest rates that are relevant to house price changes occur during dates on which there are macroeconomic news releases. Since macroeconomic news could have both direct and indirect effects on house prices, which could bias our estimates, it is necessary to control for this channel. We do so by constructing monthly surprises using Bloomberg forecasts for 24 macroeconomic news releases which Sherlund (2020) finds to be relevant for explaining changes in long-term interest rates.[14] We also include 6 other news releases which are particularly relevant for housing markets and house prices.[15] Finally, we also control for the monthly BCFF mortgage rate forecast revision, which helps predict the forecast errors; see Coibion and Gorodnichenko (2015).

[14]Bloomberg forecasts are available at least since 2001 for most major macroeconomic data releases and are based on a survey of forecasters in the week prior to the data release up until one day before the release. The surprises are constructed by taking the difference between the consensus forecast and the actual release. Each of the surprise series are standardized to have a mean of zero and a unit variance.

[15]See appendix table A.3 for the full list of the 30 macroeconomic news releases and detailed description of the BCFF shock calculation.

**Figure 3:** Changes in mortgage rates and instruments


Notes: BCFF forecast errors are orthogonalized by capturing the residuals from a regression of the 30-year fixed rate mortgage forecast error on its own lag and 30 other macroeconomic surprises from Bloomberg (see appendix table A.3).

Sources: Freddie Mac; Blue Chip Financial Forecasters; Gürkaynak et al. (2005) via Acosta (2022); Authors' analysis.

There are different ways to control for this information. One approach, as in Bauer and Swanson (2023a,b), is to pre-filter the instrument by orthogonalizing it against the additional controls. This has the advantage of 'cleaning' the instrument without any loss of degrees of freedom. However, doing so does not account for the uncertainty in the orthogonalization procedure and so could distort the standard errors. An alternative approach is to add the additional controls directly into the model itself. This has the advantage of both removing the macroeconomic news surprise component from the instrument as well as helping to capture additional variation in the residuals, thereby capturing any addition or reduction in uncertainty induced through the controls. Panel (c) in figure 3 presents the orthogonalized BCFF forecast errors and illustrates that even after controlling for macroeconomic news surprises the orthogonalized errors remain highly correlated with changes in mortgage rates, implying that much of the variation in the raw mortgage rate series is plausibly exogenous.

As an alternative set of instruments, we also consider measures of exogenous changes in monetary policy that are the most relevant for mortgage rates. First, we use the "path" factor of high-frequency monetary policy shocks obtained from movements in federal funds futures around Federal Open Market Committee (FOMC) meetings as proposed in Gürkaynak et al. (2005). The path is measured as the second principal component of the changes in interest rates over the FOMC meeting period. Gürkaynak et al. (2005) show that this measure correlates closely with changes in longer-term interest rates and captures expectations about future monetary policy changes as conveyed in meeting statements. We obtain updated "path" factor measures from Acosta (2022) through 2022. Panel (d) in figure 3 shows its evolution over time and also illustrates that it is not strongly correlated with changes in mortgage rates. Second, we consider the federal funds rate (FFR), forward guidance (FG), and large-scale asset purchase (LSAP) shocks from Swanson (2021). Finally, we also use the high-frequency movements in rates on 10-year Treasury notes around monetary policy announcements following Bauer and Swanson (2023b).

## 3.4 Housing supply elasticities and covariates

Researchers have long known that the elasticity of housing supply varies within and across cities (Baum-Snow and Han, 2019). This is attributed to land use regulation (Green et al., 2005), urban decline (Glaeser and Gyourko, 2005), and topographic constraints (Saiz, 2010). These measures are widely used in the empirical literature as exogenous variables explaining variation in local housing and labor markets (e.g., Saks, 2008). Much of the previous literature on cross-sectional variation in house price dynamics focuses on variation in the elasticity of housing supply. We consider several measures of supply elasticities including the estimated housing supply elasticity measure from Saiz (2010), the topographic interruption variable from Saiz (2010) which represents the share of land in the city that is unavailable for development, the Wharton Land Use Regulatory Index from Gyourko et al. (2021), and a measure of urban decline, the share of housing units with values below replacement cost in 1990 from Glaeser and Gyourko (2005).

# 4 Main Results

## 4.1 Stochastic specification

We employ the state-dependent local projections (LP) framework (Cloyne et al., 2023) to estimate the effect of a mortgage rate shock on the cumulative change in housing asset prices over the next $h$ months. To identify mortgage rate shocks, we build on the standard LP-IV approach (see Stock and Watson, 2018), where we instrument for the exogenous change in the mortgage rate. This variable is then interacted with the state variable of interest—a city's share of new borrowers with high monthly payment burdens—to estimate the state-dependent mortgage rate effect. Our operating hypothesis is that the mortgage rate has a negative effect on house prices that is amplified by a city's share of highly-burdened mortgage borrowers.

We use the average based on a lagged 12-month rolling window of the share of borrowers with high payment burdens to ensure that it is predetermined with respect to the mortgage rate shock, filter out noise, and eliminate seasonality. We also control for other state variables interacted with mortgage rate shocks, as recommended by Cloyne et al. (2023). These include the national DTI underwriting limit (lagged) and the city-specific elasticity of housing supply (static). We include a number of additional controls that serve a variety of purposes, including to help identify the counterfactual response of a mortgage rate shock when the state of the economy (i.e., share of borrowers with high payment burdens) is assumed not to change; see Alloza et al. (2023).

Our main empirical specification is:

$$\begin{aligned}\Delta^h p_{i,t+h} =& a_i + \beta_{1,h}\Delta r_t + \beta_{2,h}\Delta r_t \times DTI43_{i,t-1} \\ &+ \beta_{3,h}\Delta r_t \times LIM_{t-1} + \beta_{4,h}\Delta r_t \times EL_i \\ &+ \mathbf{\Gamma_h'W_{i,t}} + \mathbf{D_h'DTI43_{i,t+h}} + e_{i,t}\end{aligned} \tag{8}$$

where $\Delta^h p_{i,t+h} \equiv p_{i,t+h} - p_{i,t-1}$ is the cumulative change in log house prices after $h$ months, $\Delta r_t$ is the change in average the 30-year fixed rate mortgage rate, $LIM$ is the national DTI underwriting limit for Fannie Mae, and $EL$ is the time-invariant elasticity of housing supply from Saiz (2010). Both $DTI43$ and $LIM$ are lagged by one period to ensure that they are at least predetermined at time $t$. The vector $\mathbf{W_{i,t}}$ contains a large set of control variables including lagged changes in log house prices, lags of the two time-varying state variables, and lags of the change in the mortgage rate alone and interacted with the state variables. We include 13 lags of each of these control variables corresponding to monthly data. The vector **DTI43** controls for future values of $DTI43$ for horizons 0 to $h$ following the approach in Alloza et al. (2023). We use standard errors that are robust to both spatial and temporal auto-correlation; see Conley (1999) and Aastveit and Anundsen (2022).[16]

There are several advantages to using a state-dependent local projections framework. First is the ability to consider both linear and nonlinear effects. Second is the relative ease of modeling the parameters of interest in a single equation of what would otherwise be a complicated underlying system. This approach has become standard in the literature, and using this framework allows for direct comparisons to others in this space, including Xie (2024), Aastveit and Anundsen (2022), and Gorea et al. (2022).

An important limitation is that it requires relatively strong assumptions about the data generation process of the state-variables in order to recover the average treatment effects. Gonçalves et al. (2024) argue that the average treatment effects are in general only recovered if the state is strictly exogenous (i.e., lead / lag independent) with respect to the shock of interest. If this is not satisfied, then the state can change in response to the shock and bias the results with respect to the average treatment effect.[17] Alternatively, Alloza et al. (2023) show it is still possible to identify the average treatment effect, even if the lead exogeneity assumption is not satisfied, by controlling for future values of the state variable. Accordingly, our main specification controls for future leads in the state variable to ensure that endogeneity does not contaminate the results. We also show that our results are robust to other ways of addressing potential endogeneity concerns.

## 4.2 Main estimates

The initial results are shown in table 1. This table presents estimates for projecting cumulative house price changes at different horizons on current-period shocks, state variables, fixed

[16]Herbst and Johannsen (2024) show that in relatively small samples with highly persistent data, local projections are biased, and auto-correlation corrected standard errors are undersized. Our results are robust to other treatments of the standard errors; the standard errors we report are more conservative than Aastveit and Anundsen (2022) but less so than $i \times t$ clustering which we view as overly conservative; see table A.7 in the appendix for discussion and consideration of alternative standard errors.

[17]Gonçalves et al. (2024) show that even when the assumption is not satisfied it is still possible to recover the marginal effects of the interaction and interpret the estimates as semi-elasticities rather than average treatments (i.e., a response to a large, non-marginal shock).

effects, and controls. For our main results, we identify exogenous changes in the mortgage rates using BCFF forecast errors, and $DTI43$ using leads and other controls, thus allowing us to interpret the estimated coefficients as being plausibly identified.[18]

Unexpected mortgage rate shocks have negative effects on the cumulative log change in asset prices. The parameter on the mortgage rate increases in magnitude from -0.08 at one year to -0.54 after three years. The interaction of the shock with the high $DTI$ share is negative, significant, and economically large, suggesting that cities with a high fraction of payment-burdened borrowers face larger effects. This partial effect increases in magnitude from -0.20 to -1.25 from one to three years. The underwriting limit serves to ameliorate some of the effects of a high $DTI$ share, with its positive partial effect rising from 0.13 at one year to 1.24 at the three-year horizon.

While the interaction effect suggests that a higher share of high borrower debt-service payments affects the house price response to mortgage rate shocks, another interpretation arises when combined with the estimated effect of the interaction with the underwriting limit. If the distribution of optimal DTIs in the absence of borrowing constraints did not change over time, then controlling for the limit, the high $DTI$ share captures the cross-sectional variation in the fraction of borrowers at or nearing borrowing constraints. Accordingly, this means that DTI-based credit constraints matter both in the time series via the underwriting limit, and in the cross-section via the high $DTI$ share.[19]

Finally, the elasticity of housing supply reduces the semi-elasticity of house prices with respect to mortgage rates. This is qualitatively consistent with the results of Aastveit and Anundsen (2022) and others who have found that the elasticity of housing supply affects the dynamic response of house prices to demand shocks. In our main specification, the partial effect rises from 0.62 at one year to 1.38 at three years. This is slightly smaller than, but not statistically different with 95% confidence from, the estimate in Aastveit and Anundsen

[18] For estimates of BCFF forecast errors on mortgage rates, see table A.1. This table shows that mortgage rate shocks have positive and significant effects on the mortgage rate that peak at about 4 months at 1.45 times the initial shock, then fall to zero at about 12 months.

[19] One interesting result from table 1 is that the coefficient for $DTI43$ and the DTI limit are essentially identical and of the opposite sign at all horizons, which suggests that we could feasibly impose the restriction that the parameters are equal and opposite-signed. This would imply a new variable, $\widetilde{DTI}43 \equiv DTI43 - LIM$, which could be used instead of including $DTI43$ and $LIM$ separately. Imposing this restriction does not substantively change the empirical results.

(2022), which is about 2 for expansionary shocks.[20]

**Table 1:** Main Results

Dependent variable: $p_{i,t+h} - p_{i,t-1}$
Instrument for Δ Mortgage Rate: BCFF forecast errors

| | $h = 6$ | $h = 12$ | $h = 18$ | $h = 24$ | $h = 30$ | $h = 36$ |
|---|---|---|---|---|---|---|
| Δ Mortgage Rate | -0.02 | -0.08 | -0.25 | -0.52 | -0.55 | -0.54 |
| | (0.02) | (0.05) | (0.07) | (0.11) | (0.15) | (0.19) |
| × Share DTI>43 | -0.08 | -0.20 | -0.45 | -0.95 | -1.14 | -1.25 |
| | (0.03) | (0.08) | (0.13) | (0.18) | (0.21) | (0.24) |
| × DTI limit × 100 | 0.02 | 0.13 | 0.50 | 1.15 | 1.26 | 1.24 |
| | (0.05) | (0.11) | (0.16) | (0.24) | (0.32) | (0.39) |
| × Supply elasticity × 100 | 0.37 | 0.62 | 0.72 | 0.77 | 1.05 | 1.38 |
| | (0.10) | (0.24) | (0.38) | (0.52) | (0.64) | (0.74) |
| Observations | 60451 | 58894 | 57340 | 55789 | 54247 | 52705 |
| CBSAs | 253 | 253 | 253 | 253 | 253 | 253 |
| $R^2$ | 0.830 | 0.743 | 0.675 | 0.607 | 0.572 | 0.567 |

Notes: The table shows the effect on house prices of mortgage rate changes. The dependent variable is the cumulative log changes in Freddie Mac's house price index at horizon h = 6, 12, 18, 24, 30, and 36 months. Results are based on estimating equation 8 with city fixed effects and 13 lags of each variable (including interactions), and $h$ leads of $DTI43$, as controls. The dataset covers a panel of 253 US MSAs over the period 2000:M1–2022:M8. Mortgage rates are modeled using Blue Chip Financial Forecasters (BCFF) 1-month-ahead forecast errors for mortgage rates as instruments. The specification allows the response in house prices to differ depending on the share of Fannie Mae borrowers with back-end debt-to-income (DTI) ratios greater than 43 (12-month moving average, mean=0.22, sd=0.11), Fannie Mae DTI underwriting limits (50 or 65), and the elasticity of housing supply (mean=2.58, sd=1.44), as calculated in Saiz (2010). We use Conley (1999) standard errors that are robust to both spatial correlation and autocorrelation by employing the code developed by Hsiang (2010) and Aastveit and Anundsen (2022) and updated by Foreman (2020) for use with instrumental variables. CBSA centroids are used for distances, with the cutoff distance for the spatial correlation at 1000 kilometers. The kernel that is used to weigh the spatial correlations decays linearly with distance in all directions. The standard errors are reported in parentheses below the point estimates.
Sources: Freddie Mac; Fannie Mae; Blue Chip Financial Forecasters; Saiz (2010); Authors' analysis.

[20] We also test for asymmetry in the mortgage rate effect interacted with the supply elasticity as done by Aastveit and Anundsen (2022). We confirm an asymmetric effect in the sample that overlaps with their earlier work. However, in our full sample, we find no evidence of an asymmetric effect. Accordingly, we proceed with the implied symmetric response restriction. See appendix table A.6.

Overall, our estimates indicate important roles for the share of borrowers with high payment burdens, national underwriting limits, and the elasticity of housing supply in explaining heterogeneous effects of mortgage rate shocks on house prices.

However, partial estimates are difficult to interpret as each of the interacted covariates can be offsetting and can change within and across cities over time. We therefore perform several exercises to help illustrate the results. To build intuition, we first calculate conditional impulse responses for cities with high vs low payment burdens $\times$ high vs low supply elasticities. Next, we map the 3-year semi-elasticities every two years from 2002-2022 to view variation in the responsiveness of house prices to mortgage rate shocks over space and time. Finally, we calculate the average 1, 2, and 3-year impulse responses for each city and then take the weighted average for every month between 2000:M1 and 2023:M2.

The conditional impulse response at monthly horizon $h$ is calculated as the inner product of four parameters and conditional on the mortgage rate shock and its interaction with the values from the three different state variables:

$$\widehat{IR}(h|A) = \hat{\beta}'_{\mathbf{h}}\mathbf{A}, \tag{9}$$

where $\hat{\beta}'_{\mathbf{h}} = [\hat{\beta}_{1,h}, \hat{\beta}_{2,h}, \hat{\beta}_{3,h}, \hat{\beta}_{4,h}]$ and $\mathbf{A}' = [\Delta r, \Delta r \times DTI43, \Delta r \times LIM, \Delta r \times EL]$. The 95% confidence intervals are calculated as $\widehat{CI}(h|A) = \widehat{IR}(h|A) \pm 1.96 \times \widehat{SE}(h|A)$, where $\widehat{SE}(h|A) = \mathbf{A}'\hat{\mathbf{V}}_{\mathbf{h}}\mathbf{A}$ and $\mathbf{V}_{\mathbf{h}}$ is the $4 \times 4$ covariance matrix of the coefficient vector $\beta_{\mathbf{h}}$. We always shock the mortgage rate by one percentage point. This shock is then modified by the three state variable interactions from equation 8 and the resulting response is conditional on the values of those states. The conditional impulse responses can also be interpreted as house price-mortgage rate semi-elasticities, in log-difference form.

We choose values that represent illustrative city types to construct impulse responses. We first look at the distribution of the share of borrowers with high payment burdens per city and month and then focus on the upper and lower tails of that distribution, i.e. the top and bottom 33 percentiles of the distribution of $DTI43$. We then do the same thing for distribution of supply elasticities by city. We then classify city-month observations in one of four bins based on whether they are in the upper or lower tails of the share of indebted borrowers and also whether they are in the upper or lower tails of supply elasticities. Finally, we construct average values of each state variable from the observations in each bin and use those as inputs into the conditional impulse responses in equation (9).[21]

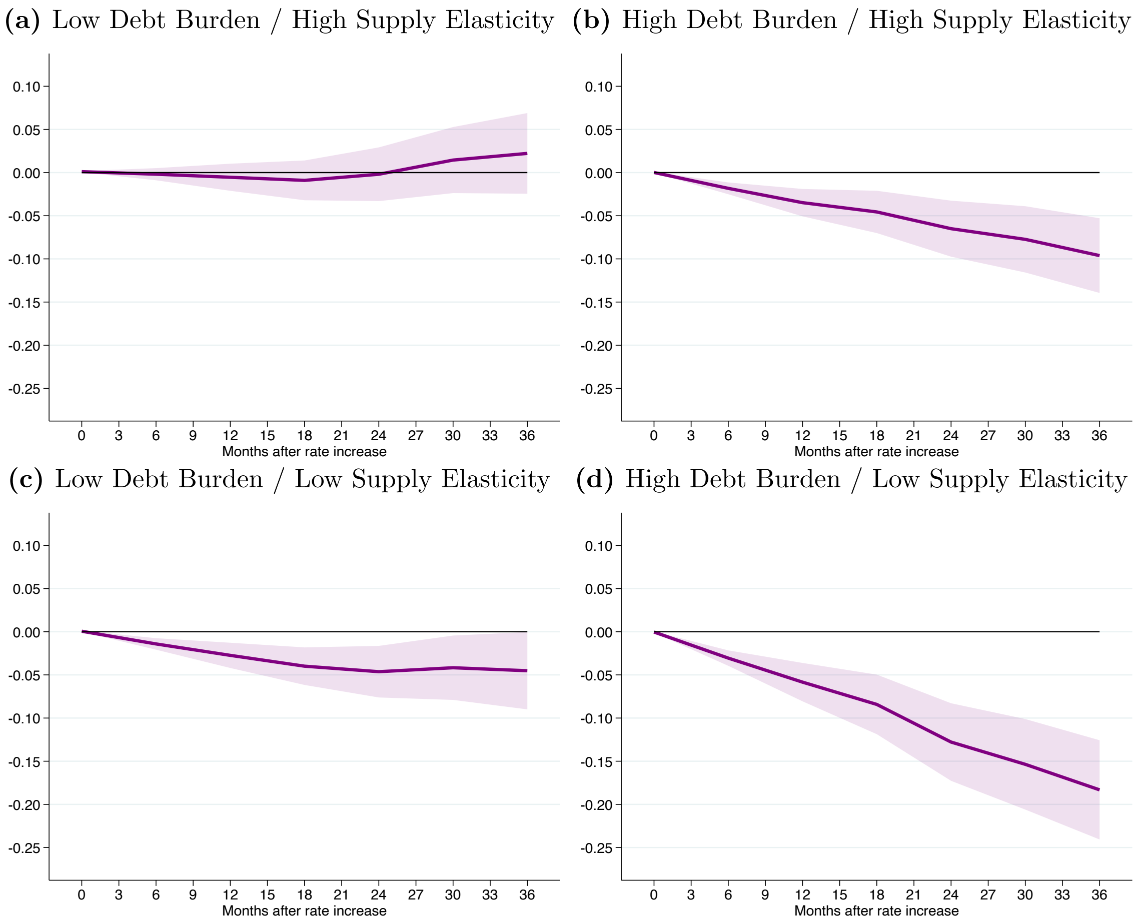
The cumulative response of local house prices to a mortgage rate shock conditional on city type is presented in Figure 4. The four types vary by the share of highly indebted borrowers and the degree of supply elasticity. Cities with a low share of debt burdened borrowers and a high supply elasticity have house prices that are much less responsive to mortgage interest rate shocks than cities with a high share of highly indebted borrowers and a low supply elasticity. Panel (a) represents a city with a low share of debt burdens and a highly responsive housing construction sector where a change in the mortgage rate has no significant effect on house prices across all horizons through 36 months. Alternatively, panel (d) represents a city with a high share of debt burdens and a low supply elasticity, where an unanticipated 100 basis point increase in mortgage rates reduces house price growth by a cumulative 18% over 3 years than it would have otherwise grown, or about 6% per year.[22]

Looking at the differences in responses across sub-figures allows us to assess the relative contributions of supply elasticity and debt payment burdens on responses. The difference between panels (a) and (c), and then (b) and (d), show the supply elasticity has somewhat smaller effects in low-DTI environments versus high-DTI environments. This difference is entirely due to differences in the joint distribution of the variables within each bin. This suggests there may be an additional interaction between the supply elasticity and debt burdens where a higher debt burden environment exacerbates the effects of a low supply elasticity and vice versa.

[21]An individual city can appear multiple times within the same bin and can also appear in different indebtedness bins if their value shifts the upper to the lower tail of indebtedness (and vice versa). Note also that for this exercise we exclude observations that don't fall in any of the four bins.

[22]Due to dimensionality considerations, we prefer the responses in the main text. We also display other renditions of cumulative responses by other dimensions. For four individual cities in particular years, see figure A.5. For several different city types in particular years, see figure A.6.

**Figure 4:** Cumulative House Price Response to a Mortgage Rate Shock Conditional on City Type




**(a)** Low Debt Burden / High Supply Elasticity **(b)** High Debt Burden / High Supply Elasticity

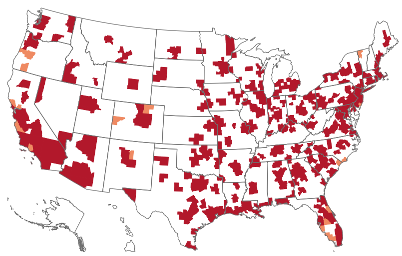
**(c)** Low Debt Burden / Low Supply Elasticity **(d)** High Debt Burden / Low Supply Elasticity

Notes: Figures present the conditional impulse response estimates from equation (9) based on a 100 basis point mortgage interest rate shock. High / low debt burden is the average of the top / bottom 33 percentiles of city-year observations respectively. Shading captures the point-wise 95% confidence intervals. Sources: Freddie Mac; Fannie Mae; Blue Chip Financial Forecasters; Saiz (2010); Authors' analysis.

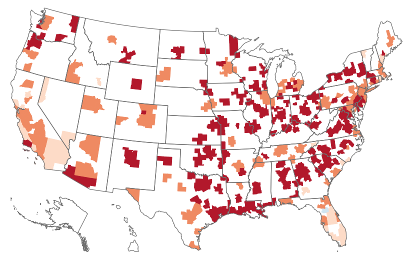
To fully appreciate the spatial and temporal differences in semi-elasticities over time, we present maps of 3-year semi-elasticities at 2-year intervals from 2002 through 2022 in figure 5. Blue and red represent cities that are the most and least sensitive to mortgage rate shocks in the given time period, respectively. Because the supply elasticity measure is constant over time, the spatial gradients can only change due to variation in $DTI43$ and $LIM$. For example, in 2004, cities in the Pacific coast and northeast states have relatively low $DTI43$s compared to Florida and Nevada, whereas just 2 years later, in 2006, the lending and house price boom was acutely felt in these locations.

**Figure 5:** Model-predicted semi-elasticities (3-year) over space and time

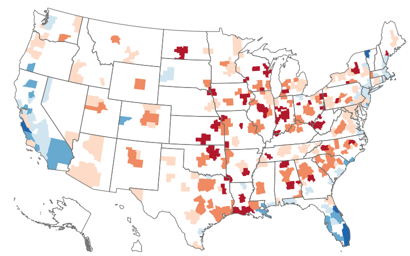
**(a)** 2002



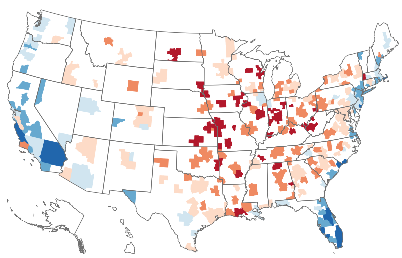
**(b)** 2004



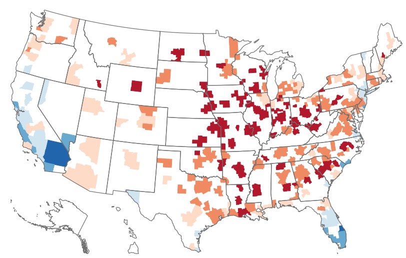
**(c)** 2006



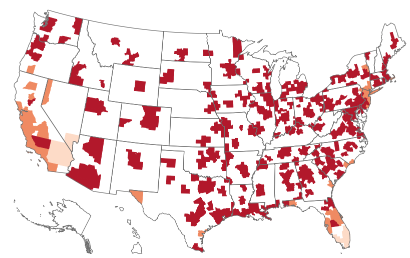
**(d)** 2008



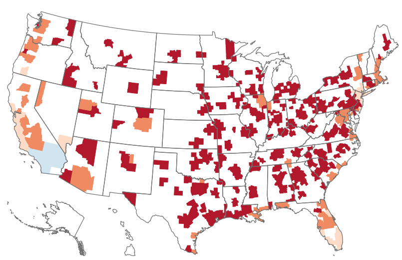
**(e)** 2010



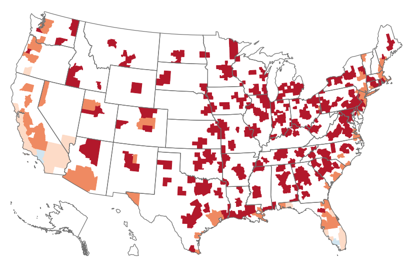
**(f)** 2012



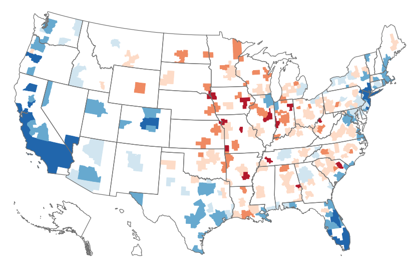
**(g)** 2014



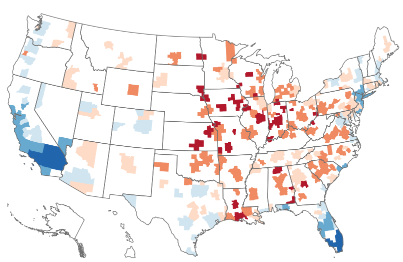
**(h)** 2016



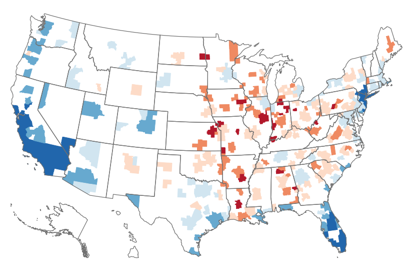
**(i)** 2018



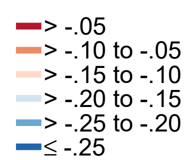
**(j)** 2020



**(k)** 2022



**(l)** Legend




Notes: This table uses estimates from table 1 and values from the time period of the subfigure title to construct 3-year (h=36) house price-mortgage rate semi-elasticities. Each cell color represents summed estimates of the following parameters from equation 8 for $h = 36$ (3 years):
$\hat{\beta}_1 + \hat{\beta}_2 DTI43 + \hat{\beta}_3 LIM + \hat{\beta}_4 EL$. The share of borrowers with DTI> 43 (12-month moving average) is from Fannie Mae's single family loan performance database for originations in June 2022. The supply elasticity measure is from Saiz (2010).

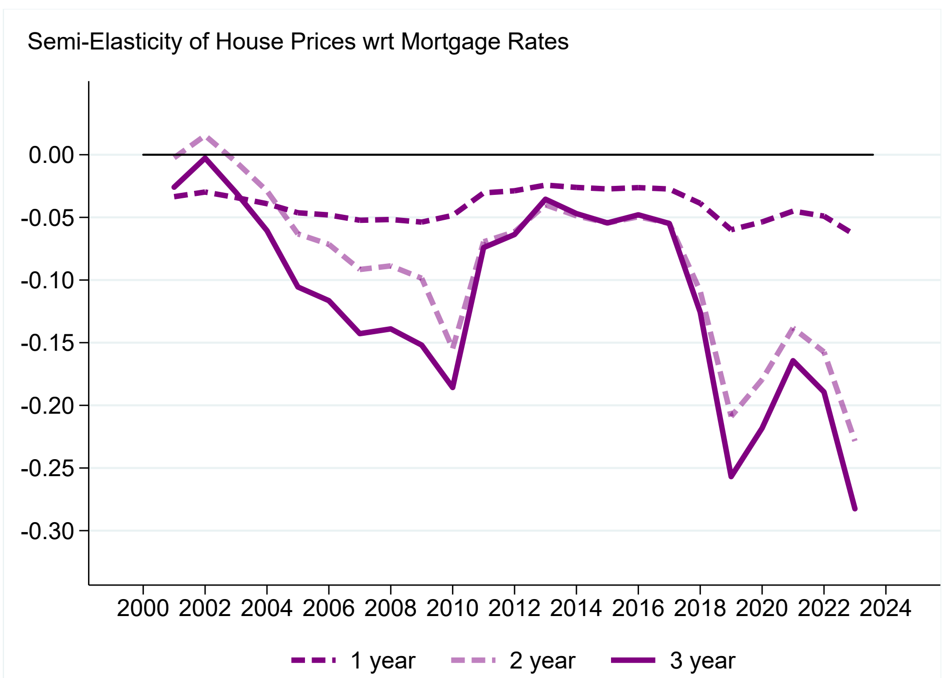
Sources: Freddie Mac; Fannie Mae; Blue Chip Financial Forecasters; Saiz (2010); Authors' analysis.

We can also see the extent to which sensitivity to mortgage rate shocks is spatially correlated.

In 2002, 2004, and 2012, $DTI43$ was highly correlated across cities (figure A.1); thus semi-elasticities were also highly correlated. On the other hand, there are large cross-sectional differences in 2006-2010 and 2018-2022. Accordingly mortgage rate shocks in these years are predicted by the model to have different effects depending on the city in question.

How has the average U.S. house price-mortgage rate semi-elasticity changed over time? It depends on the horizon. Figure 6 shows impulse responses calculated at 1, 2, and 3-year horizons, evaluated at U.S. average $DTI43$s, the U.S. DTI limit, and the U.S. average housing supply elasticity for each month between 2001:M1 and 2022:M8, weighted by the city's share of Fannie Mae new originations in the period. Because the estimates in table 1 are ordinally consistent over time, the 1-year responses are more muted than the 3-year responses. However, the partial effects do vary in importance. For example, the DTI underwriting limit has a very small relative effect on the 1-year response versus the 3-year response. Accordingly, there is very little change in 2010 from the limit tightening from 65 to 50.

**Figure 6:** Model-predicted average U.S. house price semi-elasticities (various horizons)




Notes: Figures present summed estimates of the following parameters from equation 8 for $h = 12$, 24, and 36 (1, 2, and 3 years): $\hat{\beta}_1 + \hat{\beta}_2 DTI43 + \hat{\beta}_3 LIM + \hat{\beta}_4 EL$. The share of borrowers with DTI$>$ 43 (12-month moving average) is from Fannie Mae's single family loan performance database for originations. The supply elasticity measure is from Saiz (2010).

Sources: Freddie Mac; Fannie Mae; Blue Chip Financial Forecasters; Saiz (2010); Authors' analysis.

Because the 3-year semi-elasticities present the starkest changes over time, we now discuss the series in some detail. The 3-year semi-elasticity begins at about -3% in 2001 and increases in magnitude to -18% just before the tightening of underwriting limits in 2009. In 2010, despite the tightening, the semi-elasticity falls due to the sharp drop in $DTI43$. Over the next several years, $DTI43$ continues to fall, pushing the semi-elasticity to about -5%, where it hovers until 2017, after which borrowers began increasing their debt payment burdens, presumably due to the relaxing of DTI overlays from 45 to 50. $DTI43$s then rise and fall inversely with interest rates through the remainder of the sample in 2022, when the U.S. average 3-year semi-elasticity is at its 21st-century high of about -28%.[23]

### 4.3 Discussion

Our results imply the share of new mortgage borrowers with extreme debt service payments amplifies the propagation of mortgage rate shocks to house prices. Between 2001 and 2023, the average U.S. house price-mortgage rate semi-elasticity rose from -3% to -28%, due to tighter DTI-based underwriting and higher monthly mortgage payment burdens. Accordingly, the relative importance of housing supply measures in explaining the effects of mortgage rate shocks has declined over time.

Because DTI includes all debt, not just mortgages, there are spillovers from other sectors into housing. For example, student loans, credit card debt, auto loans, property taxes, and homeowners' insurance all contribute to household balance sheet liabilities. Policies, such as student loan forgiveness or local property tax rate changes, thus directly affect the propagation of mortgage rate shocks to house prices.

How do our estimates compare with those in the literature? Williams (2015) provides a literature review of estimated semi-elasticities in papers written in 2015 and before. This review shows a range of long-run semi-elasticities of -1.7% to -10.8%, with a median estimate of -7.8%. Aastveit and Anundsen (2022), who uses U.S. data through 2007, report a high-end estimate of -7% after 2 years in the most housing supply-elastic cities. Glaeser et al. (2012) estimates a semi-elasticity between -7% and -8%.

Using results from figure 6, our estimates fit within the range of these earlier estimates in the pre-2016 period. Our 2-year semi-elasticities in this sub-sample are around -7%,

[23]Note that the results are slightly smaller but broadly unchanged if we use the median city instead of weighting by originations.

while ranging between -2% and -15%. This gives credibility to our post-2016 estimates which become much larger, with a 2-year semi-elasticity of -23% in 2022. Overall, while our estimates near the end of our sample are higher than those in the literature, they are higher due to fluctuations in DTIs and underwriting limits, not marginal effects. Near the beginning of our sample, which overlaps with much of the literature, our estimates are well within the previously-established range. This pattern is also generally consistent with Paul (2020) who looks at the time-varying effects of monetary policy. Thus, we interpret our results as helping to explain why the effectiveness of monetary policy varies over time.

Why did house price appreciation not fall further in 2023-2024 due to the interaction of high debt burdens and large mortgage rate increases? First, it should be noted that appreciation did fall substantially, from 17% in the median city in 2022 to 6% in 2023. There are also other dynamics that complicate simple counterfactual predictions. Changes to non-mortgage rate user costs also affect house prices. For example, appreciation expectations rose steadily between 2022 and 2024.[24] This expected appreciation effect may have been large because inflation was relatively high and housing inventories were relatively low due to "rate lock-in" effects from rapidly rising mortgage rates (Fonseca and Liu, 2024; Batzer et al., 2024). House prices are also still adjusting to the changes in remote work arrangements since the pandemic; see Howard et al. (2023). These dynamics could imply weaker effects of the 2022 interest rate changes on future price appreciation.

# 5 Robustness and Extensions

In this section, we demonstrate the robustness of our main specification to alternative instrumental variables, state variables, and controls. We also discuss the role of omitted variables in state-dependent responses to mortgage rate shocks. The supplemental appendices test for asymmetric responses and consider the use of alternative standard errors in inference.

[24]The user cost literature has additional predictions regarding the effects of interest rates on house prices. Himmelberg et al. (2005) demonstrates how the closer the user cost is to 0, the higher the semi-elasticity of house prices with respect to mortgage rates. Accordingly, the semi-elasticity will be higher when the mortgage rate level is low and when expected appreciation is high. As a corollary, insofar as the ratio of housing rental prices to asset prices ("cap rates") reflects user costs, the semi-elasticity will also be negatively related to the cap rate. These confounding factors should be considered in any empirical analysis, in addition to the aforementioned DTI-related factors and the elasticity of housing supply. We address this possibility and show our main results to be robust in appendix table A.5.

## 5.1 Alternative approaches to account for DTI endogeneity

An important concern is whether we have fully accounted for the endogeneity of $DTI43$ with respect to mortgage rate changes. As discussed above, DTI is affected by interest rates directly through monthly mortgage payments for unconstrained borrowers, and indirectly through the change in the fraction of constrained borrowers and any resulting changes in house prices. We account for this both indirectly and directly using controls for lagged interest rates, house price changes, and interactions as well as leads of $DTI43$ to control for future feedback. The focus here is on the robustness of our estimates to alternative approaches and control sets for addressing the likely endogeneity.

We examine the extent to which our estimates change when considering alternative specifications for dealing with endogeneity. In our baseline specification, following the approach in Alloza et al. (2023), we control for the future path of $DTI43$. This means we control for future changes in the state variable, regardless of its source. Our first alternative ignores possible lead endogeneity by not controlling for future values. Second, we use lagged $DTI43$ from three years prior which is exogenous to all future interest rate changes over the horizons of interest; see Supplemental Appendix D for more details. This should allow us to recover the average treatment effect uncontaminated by feedback. Third, we eliminate any temporal variation in $DTI43$ such that our results are only identified off of the cross-sectional variation across cities. We do this in two ways: first, using the city-level sample average, and second, the average in 2000 which is completely predetermined with respect to our sample.

The results in table 2 indicate that our baseline results are quite robust to other ways of dealing with endogeneity concerns. The estimated effect size of the interaction ranges from -1.74 to -0.81 and lies within the two standard deviation range of the baseline estimate of -1.25. Most of these estimates are slightly larger than the baseline estimates except for the specifications which ignore endogeneity and when the initial measure of DTI from 2000 is used. Thus, although DTI is not strictly exogenous with respect to mortgage rate shocks, using leads to control for endogeneity provides reasonable estimates.

**Table 2:** Average treatment effect robustness

Dependent variable: $p_{i,t+36} - p_{i,t-1}$

| | | | | | |
|---|---|---|---|---|---|
| $DTI43$ Variable: | 12-mo Ave. | 12-mo Ave. | 12-mo Ave. | Mean | Initial |
| $DTI43$ State interaction lag: | 1 | 1 | 36 | N/A | N/A |
| $DTI43$ Leads as controls: | Yes | No | No | No | No |
| $\Delta$ Mortgage Rate | -0.54 | -0.62 | -1.31 | 0.15 | -0.01 |
| | (0.19) | (0.19) | (0.21) | (0.21) | (0.18) |
| $\times$ DTI variable (column) | -1.25 | -1.14 | -1.49 | -1.74 | -0.81 |
| | (0.24) | (0.26) | (0.31) | (0.53) | (0.21) |
| $\times$ DTI limit $\times$ 100 | 1.24 | 1.27 | 2.69 | 0.08 | 0.07 |
| | (0.39) | (0.41) | (0.45) | (0.26) | (0.26) |
| $\times$ Supply elasticity $\times$ 100 | 1.38 | 1.65 | 0.16 | 1.02 | 2.09 |
| | (0.74) | (0.76) | (0.99) | (0.51) | (0.63) |
| Observations | 52705 | 52705 | 43579 | 52705 | 52700 |
| CBSAs | 253 | 253 | 253 | 252 | 252 |
| $R^2$ | 0.567 | 0.540 | 0.470 | 0.528 | 0.520 |

Notes: See table 1 notes for details on the sample, variable definitions, and estimator. The dependent variable is the cumulative 3-year change in log-house prices. Column 1 includes contemporaneous $DTI43$ and all leads up to horizon $h$. Column 2 is same as Column 1 except it excludes leads. Column 3 uses 36-period lagged $DTI43$ in place of the 1-period lagged variable. Column 4 uses the average $DTI43$ share from 2000-2022. Column 5 uses the average $DTI43$ share across the 12 months of 2000.
Sources: Freddie Mac; Fannie Mae; Blue Chip Financial Forecasters; Saiz (2010); Authors' analysis.

### 5.2 Alternative instruments

It is common to use measures of monetary policy surprises either as instruments or as direct measures of interest rate shocks. This approach has been used by Aastveit and Anundsen (2022), Gorea et al. (2022), Xie (2024), and others to model house prices. We noted in figure 3 that while monetary policy shocks are plausibly exogenous, they may lack relevance, with a correlation of 0.22 with mortgage rate changes. Mortgage rates are partially determined by Treasury rates (especially 7 and 10 year notes) but are also driven by shocks to mortgage prepayment rates, credit risk perceptions, and other supply and demand factors in the primary mortgage market. Due to these factors, we use forecast errors as shocks for our main results, as these incorporate not just monetary policy surprises, but other types of shocks.

Table 3 takes equation 8 and presents estimated parameters using several identification strategies. First, no IV is used and mortgage rate changes are interpreted as shocks. Next, we use our preferred forecast error shock as instruments, both the standard version and orthogonalized with respect to 30 other macroeconomic surprises. We also consider a number of alternative monetary policy shocks, including the direct effects on 10-year rates from Bauer and Swanson (2023b, "B&S"), the "Path" shock from Gürkaynak et al. (2005, "GSS") as updated by Acosta (2022), and derived monetary policy shocks for the federal funds rate (FFR), forward guidance (FG), and large scale asset purchases (LSAP) from Swanson (2021).[25]

**Table 3:** Alternative Instruments

Dependent variable: $p_{i,t+36} - p_{i,t-1}$

| | | Blue Chip Forecast Errors | | B&S | GSS | Swanson (2021) | | |
|---|---|---|---|---|---|---|---|---|
| Instrument: | None | Standard | Orthog. | T10 | Path | FFR | FG | LSAP |
| $\Delta$ Mortgage Rate | -0.43 | -0.54 | -0.26 | -1.70 | -2.76 | -2.16 | -2.64 | -1.94 |
| | (0.14) | (0.19) | (0.19) | (0.67) | (0.63) | (0.92) | (0.77) | (0.95) |
| $\times$ Share DTI>43 | -1.03 | -1.25 | -1.04 | -2.83 | -1.50 | 0.26 | -5.25 | -1.96 |
| | (0.19) | (0.24) | (0.27) | (0.89) | (0.65) | (1.76) | (1.25) | (1.24) |
| $\times$ DTI limit $\times$ 100 | 0.99 | 1.24 | 0.68 | 4.20 | 4.75 | 3.97 | 6.43 | 4.47 |
| | (0.29) | (0.39) | (0.40) | (1.51) | (0.98) | (2.16) | (1.73) | (2.19) |
| $\times$ Supply elasticity $\times$ 100 | 0.73 | 1.38 | 1.59 | -2.58 | 1.88 | -3.60 | -1.50 | -2.92 |
| | (0.55) | (0.74) | (0.78) | (2.55) | (2.29) | (5.66) | (3.54) | (3.20) |
| Observations | 52705 | 52705 | 52705 | 52705 | 52705 | 52705 | 52705 | 52705 |
| CBSAs | 253 | 253 | 253 | 253 | 253 | 253 | 253 | 253 |
| $R^2$ | 0.568 | 0.567 | 0.567 | 0.544 | 0.510 | 0.454 | 0.504 | 0.513 |

Notes: See table 1 notes for details on the sample, variable definitions, and estimator. The dependent variable is the cumulative 3-year change in log-house prices. Mortgage rate changes are modeled without instruments in column 1, using Blue Chip Financial Forecasters (BCFF) 1-month-ahead forecast errors for mortgage rates as instruments, raw in column 2, and orthogonalized in column 3. Column 4 uses high frequency shocks to 10-year Treasury Notes around FOMC meetings as calculated by Bauer and Swanson (2023a, "B&S") Column 5 uses the "Path" monetary policy shock from Gürkaynak et al. (2005, "GSS") as updated by Acosta (2022). Columns 6-8 are the shocks conventional (FFR) and unconventional (Forward Guidance (FG) and LSAP shocks from Swanson (2021).

Estimates across the alternative identification strategies are remarkably consistent. Al-

[25]We also considered the LSAP shock from Jarociński (2024). The results (not shown) are very similar to the LSAP shock from Swanson (2021) and are available upon request.

though, the direct effects of mortgage rates are generally estimated to be much larger when using the monetary policy shocks as instruments. For the $DTI43$ interaction, estimates across the various specifications are all negative and significant, except for the federal funds rate which is not statistically different than zero. The DTI limit interaction also has consistent signs, albeit larger estimated effects for the monetary policy shocks. In contrast, the supply elasticity is not usually statistically different than zero for non-forecast error identification.

### 5.3 Alternative DTI measures

It is also possible that our main results are sensitive to the DTI measures used as state variables and controls. In our main specification, our state variable that identifies heterogeneous responses across cities is the lagged 12-month moving average of the share of Fannie Mae borrowers with back-end DTIs greater than 43.

To assess the robustness of our preferred measures, we first explore three alternative measures: (1) $DTI43$ without its moving-average representation; (2) the share of borrowers with DTI greater than 36 ($DTI36$); and (3) the average overall DTI. The parameter estimates in table 4 show the results of these models. Using lagged $DTI43$ instead of the lagged MA(12) representation results in a decline in the parameter estimate, presumably due to noise. The $DTI36$ and $DTI$ parameters have a negative sign and statistical significance, but with smaller magnitudes than $DTI43$ because the average value of $DTI43$ is smaller than $DTI36$ and $DTI$.

We also consider DTI measures from the National Mortgage Database (NMDB) in case our Fannie Mae DTI measures prove unrepresentative. The NMDB is a one-in-twenty representative sample of all closed-end first-lien mortgages issued in the United States since 1998 and thus covers the entire U.S. mortgage market. The first $DTI43$ measure returns to the lagged 12-month moving-average representation and includes all Enterprise loans, not just Fannie Mae. Estimates are nearly identical to the Fannie Mae-only measure. The second measure is calculated the same way as the first, but uses all newly originated mortgages, which include FHA, VA, and private loans, including those in private-label securities. Again, the estimates shown in table 4 are similar to our baseline results.

**Table 4:** Alternative DTI measures

| | | | | | | |
|---|---|---|---|---|---|---|
| Dependent variable: | $p_{i,t+36} - p_{i,t-1}$ | | | | | |
| Instrument for Δ Mortgage Rate: | BCFF forecast errors | | | | | |
| DTI sample: | FNM | FNM | FNM | FNM | FNM+FRE | All |
| MA(12): | Yes | No | No | No | Yes | Yes |
| DTI Variable: | DTI43 | DTI43 | DTI36 | DTI | DTI43 | DTI43 |
| Δ Mortgage Rate | -0.54 | -0.29 | -0.29 | -0.06 | -0.40 | -0.42 |
| | (0.19) | (0.16) | (0.16) | (0.16) | (0.16) | (0.15) |
| × DTI variable (column) | -1.25 | -0.69 | -0.32 | -0.92 | -0.94 | -0.80 |
| | (0.24) | (0.15) | (0.13) | (0.46) | (0.21) | (0.25) |
| × DTI limit × 100 | 1.24 | 0.55 | 0.56 | 0.49 | 0.82 | 0.84 |
| | (0.39) | (0.30) | (0.29) | (0.29) | (0.33) | (0.30) |
| × Supply elasticity × 100 | 1.38 | 2.08 | 1.71 | 1.91 | 2.14 | 1.91 |
| | (0.74) | (0.74) | (0.75) | (0.74) | (0.87) | (0.82) |
| Observations | 52705 | 52705 | 52705 | 52705 | 51605 | 51605 |
| CBSAs | 253 | 253 | 253 | 253 | 253 | 253 |
| $R^2$ | 0.567 | 0.567 | 0.510 | 0.538 | 0.515 | 0.517 |

Notes: See table 1 notes for details on the sample, variable definitions, and estimator. The dependent variable is the cumulative 3-year change in log-house prices. The specification allows the response in house prices to differ depending on various DTI measures, including the Fannie Mae share of borrowers with $DTI > 43$ (MA[12] and in the level), $DTI > 36$, and the mean DTI, respectively. The FNM+FRE and All DTI samples use $DTI43$s constructed using the National Mortgage Database.
Sources: Freddie Mac; Fannie Mae; Blue Chip Financial Forecasters; National Mortgage Database; Authors' analysis.

### 5.4 Omitted variable bias in state variable interactions

When applied to house prices, the empirical approach that motivates the LP-IV framework in this paper typically only uses the elasticity of housing supply as a single state variable (e.g., Aastveit and Anundsen, 2022). Our model encompasses this approach and adds two other state variables, the underwriting DTI limit and the share of borrowers with extreme DTIs. We show here that failure to model each of these state variables together may introduce substantial omitted variable bias, as predicted (and cautioned) by Cloyne et al. (2023).

The elasticity of housing supply measure of Saiz (2010) has a -45% cross-city correlation with extreme shares of debt payment burdens in 2022. A one point increase in this elasticity measure is associated with a 2.6 percentage point decrease in the share of borrowers with DTIs greater than 43.[26] While these are only reduced form relationships, we surmise that low elasticities increase both house prices and $DTI43$. In a model where both the elasticity of housing supply and the share of high DTI borrowers matter, failure to account for one or the other will result in omitted variable bias. In models with both the elasticity of housing supply and $DTI43$ such as our main specification, the variable $DTI43$ may act as a partial mediator for the supply elasticity.

**Table 5:** Alternative interaction sets

| | | | | |
|---|---|---|---|---|
| Dependent variable: | $p_{i,t+36} - p_{i,t-1}$ | | | |
| Instrument for $\Delta$ Mortgage Rate: | BCFF forecast errors | | | |
| Interaction set | None | DTI | Elasticity | All |
| $\Delta$ Mortgage Rate | -0.13 | -0.94 | -0.19 | -0.54 |
| | (0.02) | (0.20) | (0.04) | (0.19) |
| $\times$ Share DTI>43 | | -1.71 | | -1.25 |
| | | (0.26) | | (0.24) |
| $\times$ DTI limit $\times$ 100 | | 2.13 | | 1.24 |
| | | (0.40) | | (0.39) |
| $\times$ Supply elasticity $\times$ 100 | | | 2.56 | 1.38 |
| | | | (0.92) | (0.74) |
| Observations | 52705 | 52705 | 52705 | 52705 |
| CBSAs | 253 | 253 | 253 | 253 |
| $R^2$ | 0.326 | 0.545 | 0.329 | 0.567 |

Notes: See table 1 notes for details on the sample, variable definitions, and estimator. The dependent variable is the cumulative 3-year change in log-house prices.
Sources: Freddie Mac; Fannie Mae; Blue Chip Financial Forecasters; Authors' analysis.

[26] Other measures and determinants of the elasticity of housing supply are correlated as well. See appendix figure A.8. We also use these alternative supply elasticity variables in place of the Saiz (2010) elasticity measure in regressions, including the urban decline measure of Glaeser and Gyourko (2005), the unavailable land measure of Saiz (2010), the Wharton Land Use Regulatory Index described by Gyourko et al. (2021), and the sensitivity instrument constructed by Guren et al. (2021). Each measure, with model estimates in table A.9, shows a robust elasticity parameter estimate.

Table 5 shows how failure to incorporate DTI variables or the supply elasticity variable can cause omitted variable bias. Comparing the DTI parameters in the "DTI" column to the "All" column, we see the $DTI43$ parameter falls by 26% and the DTI limit parameter falls by 38%. Then, comparing the elasticity parameter in the "Elasticity" column to the "All" column, we see the elasticity parameter falls by 37%. Thus, both DTI and supply elasticity should be included as state variables to avoid omitted variable bias.

### 5.5 Additional controls

Some variables excluded from the main specification may correlate simultaneously with the mortgage rate shocks, their interactions, and house prices. This could induce omitted variable bias in the parameters of interest. To assess this, we consider three additional control variable sets beyond our main control set. We also consider additional state variable control sets, which include interactions with mortgage rate shocks, leads, and lags similar to the DTI variables considered.

In our baseline specification, we have 253 CBSA-level fixed effects, and 13 lags of house price appreciation, the change in mortgage rate, and the change in mortgage rate interacted with each of the three state variables. We also include 13 lags of $DTI43$. We do not include lags of the DTI limit because it is a step function and thus could introduce spurious dynamics into the estimated model.

The shock control set is 30 contemporaneous macroeconomic news surprises and the lagged forecast error for the mortgage rate surprise. These are the same variables used to orthogonalize the forecast error shock instrument in figure 3 and table 3. The news surprises, entered into the main house price appreciation equation, serve to both orthogonalize the shock variable and soak up any residual price variation, thereby improving the efficiency of the other estimates. Appendix table A.2 shows parameters change slightly and standard errors decrease relative to the standard control set, but qualitative findings are unchanged.

The local control set consists of 13 lags of CBSA-level changes in employment (monthly) and wage earnings (quarterly) from the Bureau of Labor Statistics' Quarterly Census of Employment and Wages. These two variables capture variation in local economic conditions that are not already incorporated into lags of local appreciation. Estimates using these controls are of similar sign, significance, and magnitude.

In the model with time period fixed effects, all national movements in house prices and covariates are subsumed. Thus, the effect of the change in the mortgage rate, both in the level and interacted with the DTI limit, is no longer identified. In this model, both the $DTI43$ and the supply elasticity are of smaller magnitude but statistically significant, suggesting that these variables play an important role in explaining the heterogeneous effects of mortgage rate shocks across cities.

Finally, we consider other state-variable controls. These consist of various mortgage borrower LTV and credit score measures, interactions with mortgage rate changes, and leads and lags to account for potential state-variable endogeneity. Appendix table A.8 shows that the $DTI43$ parameter estimates are robust even when accounting for the share of borrowers with high ($> 90$) LTVs and low ($< 660$) credit scores in the National Mortgage Database.

# 6 Conclusion

This paper offers an additional explanation for house price dynamic heterogeneity and a new important channel for monetary policy transmission: mortgage borrower indebtedness. We offer theoretical and empirical evidence that high mortgage borrower debt service burdens amplify the effects of mortgage rate shocks on house prices.

In our conceptual framework and discussion, we argue that this occurs because borrowers with high debt-service-to-income ratios (DTIs) face amplified changes to funding costs due to credit risk layering and DTI underwriting constraints. This increases the sensitivity of household borrowing to mortgage rate shocks; in aggregate, this affects local housing demand beyond the partial effect of changing mortgage rates. Thus, high DTIs amplify the effects of mortgage rate shocks on house prices, including those caused by monetary policy. Because the share of borrowers with high DTIs varies both within and across markets over time, shock propagation is state-dependent.

Empirically, we use the state-dependent local projections framework of Cloyne et al. (2023), with identification strategies recommended by Stock and Watson (2018), Alloza et al. (2023), and Gonçalves et al. (2024), to estimate the causal effect of mortgage rate shocks on house prices in cities with different time and cross-sectionally varying DTI characteristics. Crucially, our model includes various state interaction controls which allow our model to encompass those in the prior literature, including Aastveit and Anundsen (2022) and Xie (2024), who focus exclusively on the elasticity of housing supply as a state variable.

The implications of our analysis are crucial to understanding the transmission of monetary policy and other interest rate shocks to the real economy via the housing market. When an economy consists of a set of housing markets with borrowers who face high debt-service payments, monetary policy can have amplified effects on national house prices. This has consequences for mortgage default rates, as house prices affect the mark-to-market leverage ratio on mortgages, and consumption, as households consume a proportion of accumulated home equity via cash-out refinances (Iacoviello, 2005; Mian et al., 2013). Thus, our research helps improve the understanding of the propagation of interest rate shocks on house prices and the macro-economy across space and time.

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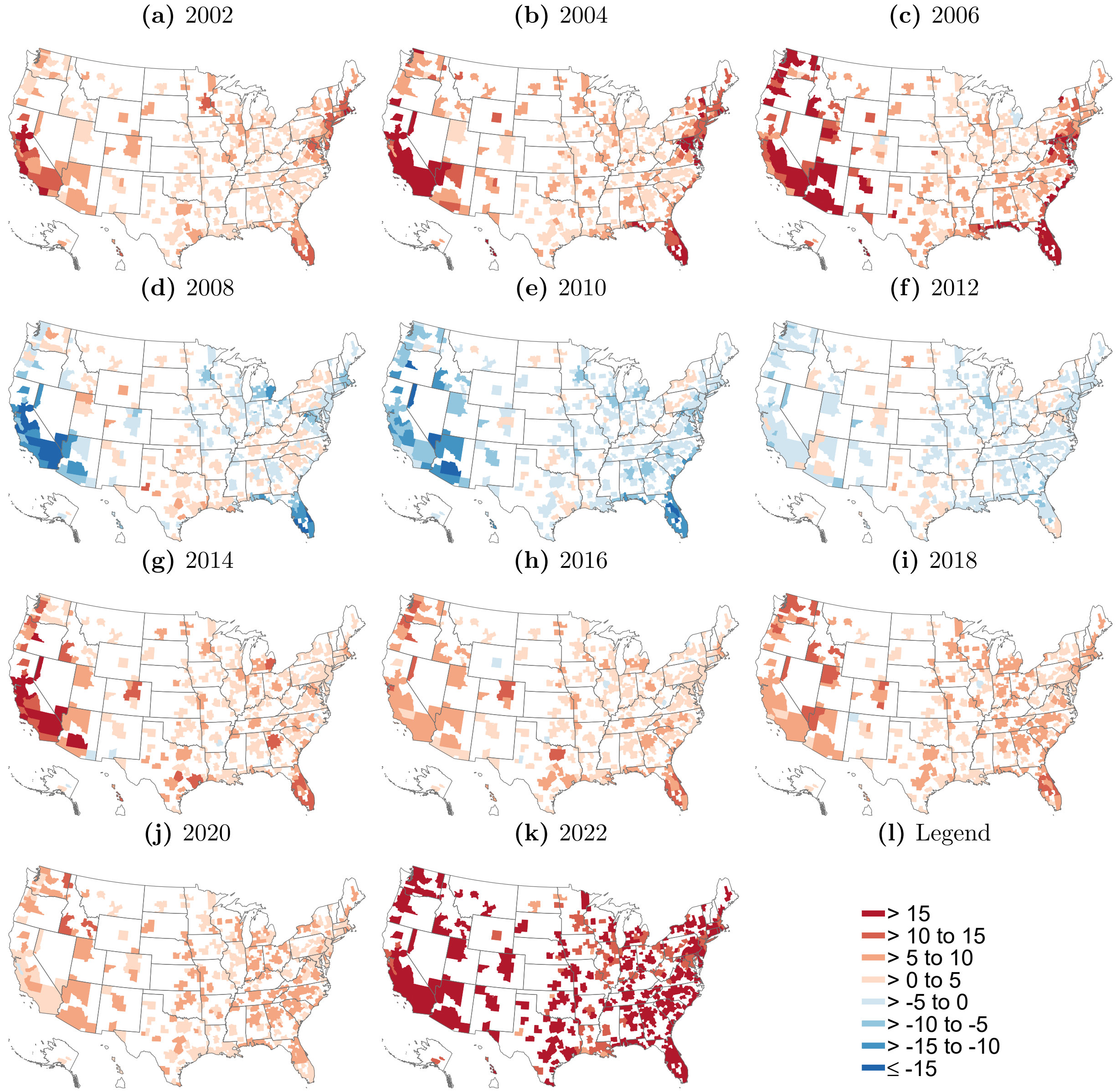
# Online Appendix

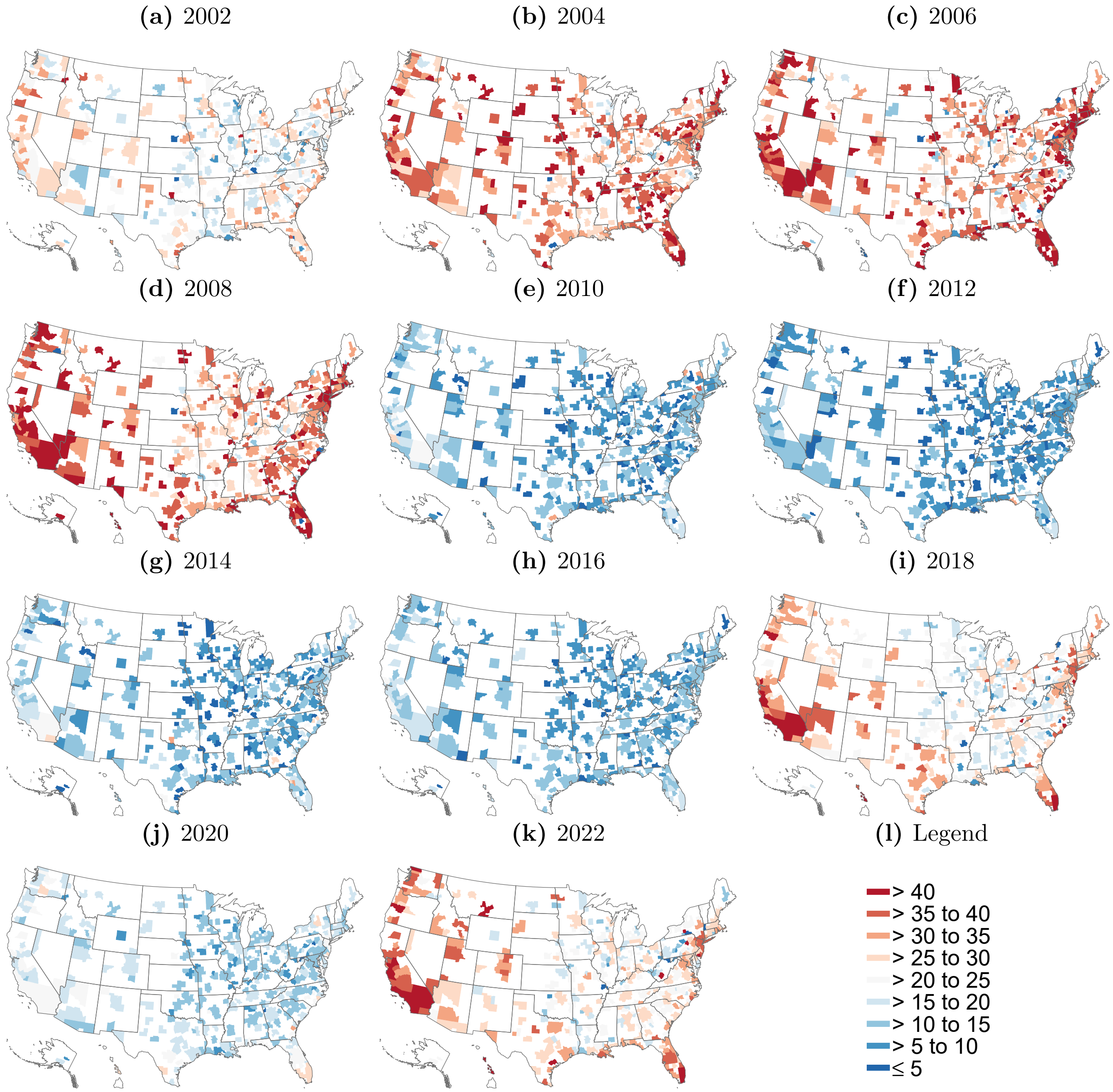
## A Supplemental tables and figures

**Figure A.1:** Average annual house price appreciation, prior 2 years



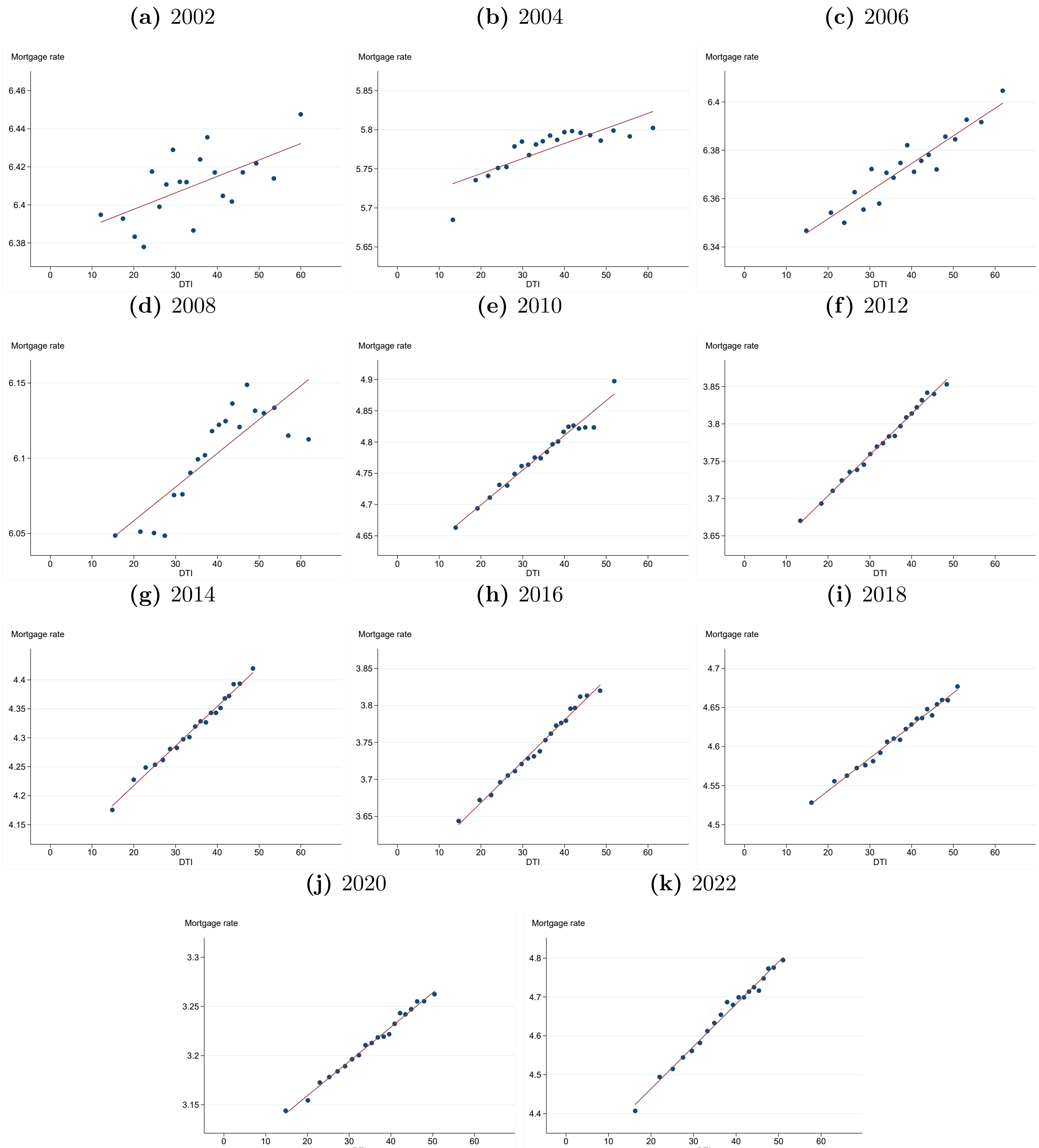

Sources: Fannie Mae; Authors' analysis.

**Figure A.2:** High (> 43) DTIs




Sources: Fannie Mae; Authors' analysis.

**Figure A.3:** DTI - mortgage rate conditional bin-scatter plots

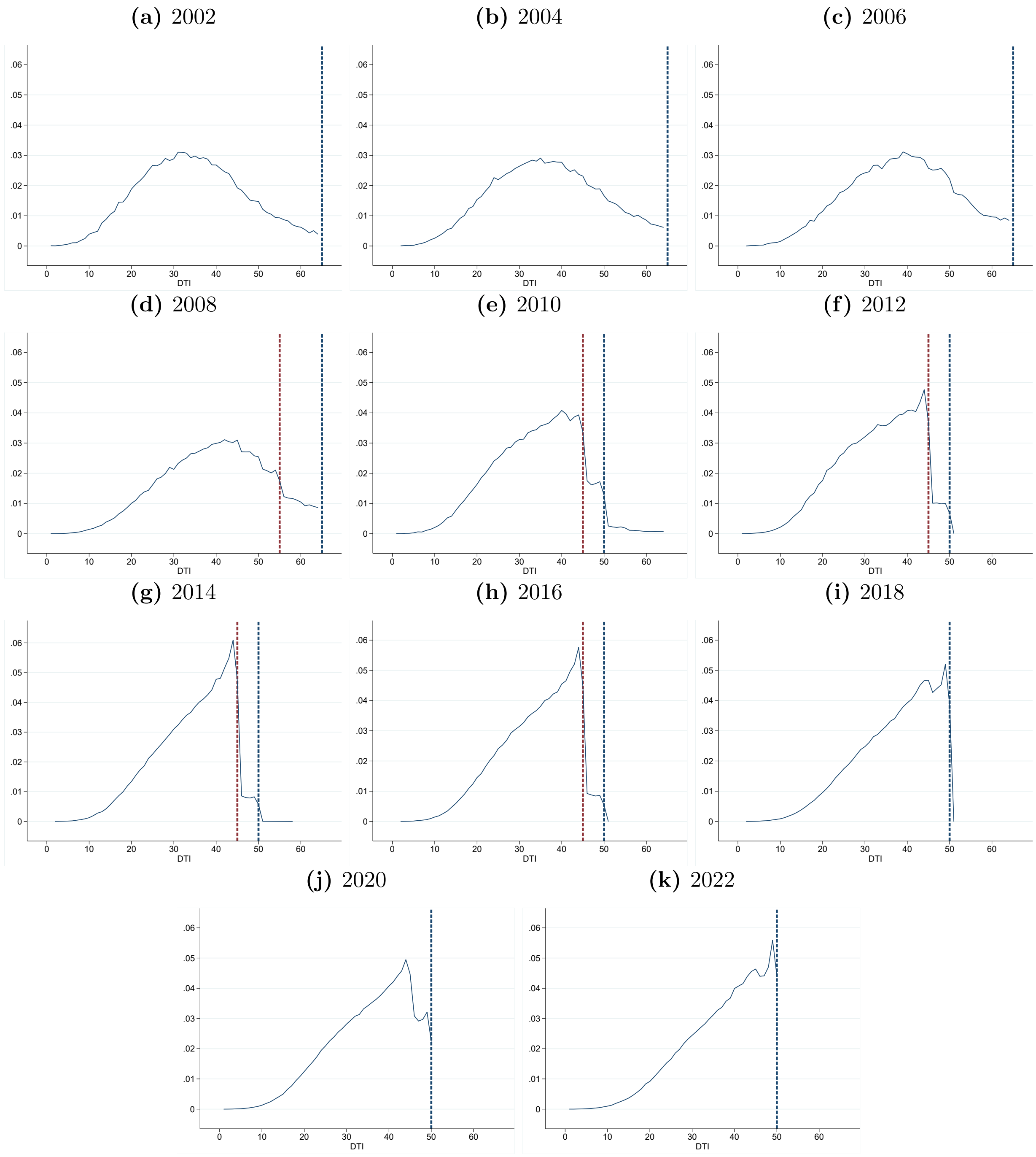



**(a)** 2002 **(b)** 2004 **(c)** 2006 **(d)** 2008 **(e)** 2010 **(f)** 2012 **(g)** 2014 **(h)** 2016 **(i)** 2018 **(j)** 2020 **(k)** 2022

Notes: The scatter plot is calculated using the "binscatter" command in STATA (e.g. Chetty et al., 2014) using the function written by Jessica Laird and available at `https://michaelstepner.com/binscatter`. The data include all owner-occupier purchase-money mortgages, and the binned-scatterplot is conditional on 8 bins of LTV, 8 bins of credit score, and a first-time homebuyer dummy. Each point represents a 5% sample bin.

Sources: Fannie Mae; Authors' analysis.

**Figure A.4:** DTI distribution with overlay and limit



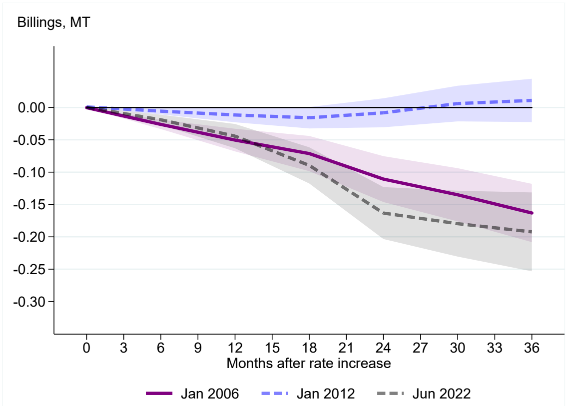

**(a)** 2002 **(b)** 2004 **(c)** 2006 **(d)** 2008 **(e)** 2010 **(f)** 2012 **(g)** 2014 **(h)** 2016 **(i)** 2018 **(j)** 2020 **(k)** 2022

Notes: The red dashed line is the DTI overlay start, and the blue dashed line is the hard DTI limit. If there is no overlay in a particular year its because it does not exist (2018-2022) or is not publicly known (2000-2007) for that particular year.

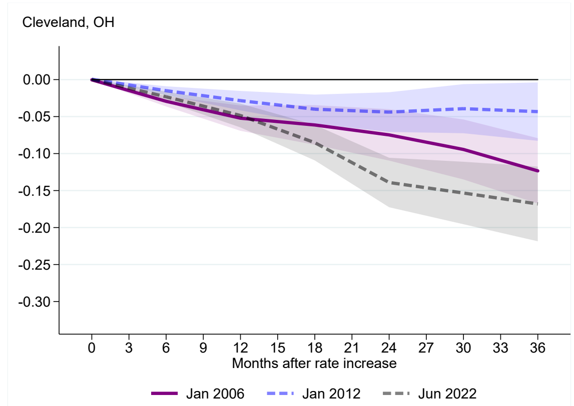
Sources: Federal Housing Finance Agency; Fannie Mae; Authors' analysis.

**Figure A.5:** Model-predicted within-city variation in house price semi-elasticities

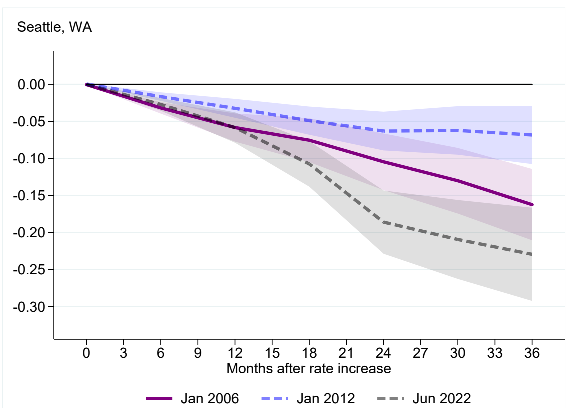
**(a)** Billings, MT



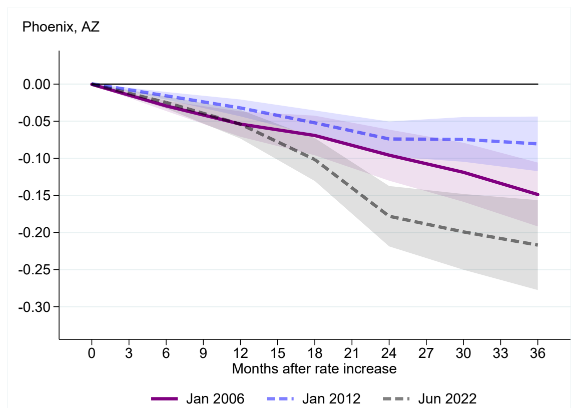

**(b)** Cleveland, OH




**(c)** Seattle, WA




**(d)** Phoenix, AZ

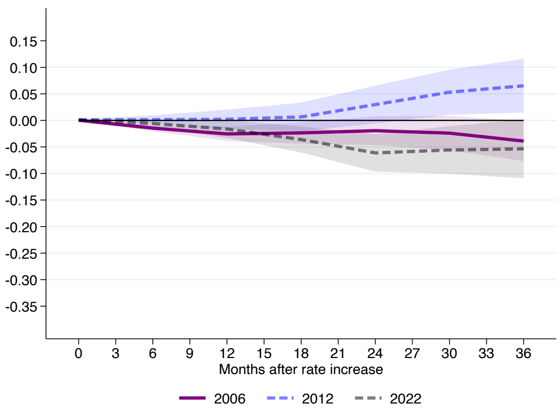



Notes: Figures present summed estimates of the following parameters from equation 8 for $h$= 6, 12, 18, 24, 30, and 36 months: $\hat{\beta}_{1,h} + \hat{\beta}_{2,h} DTI43_{i,t-1} + \hat{\beta}_{3,h} LIM_{t-1} + \hat{\beta}_{4,h} EL_i$. The share of borrowers with DTI> 43 (12-month moving average) is from Fannie Mae's single family loan performance database for originations in June 2022. The supply elasticity measure is from Saiz (2010).

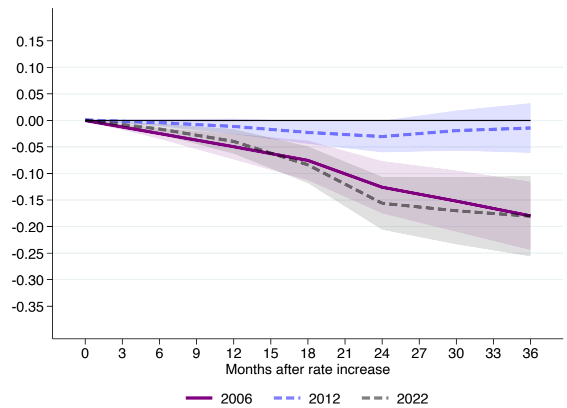
Sources: Freddie Mac; Fannie Mae; Blue Chip Financial Forecasters; Authors' analysis.

**Figure A.6:** Cumulative House Price Response to a Mortgage Rate Shock Conditional on City Type

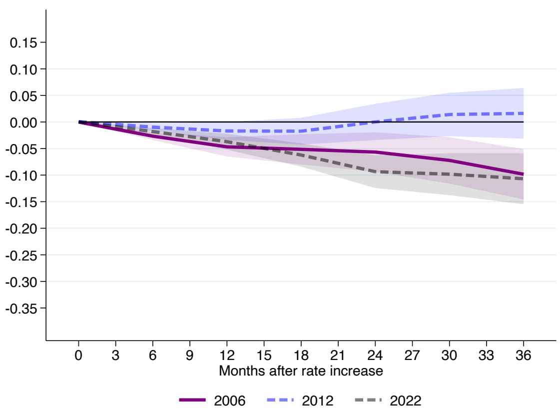
**(a)** Low Debt Burden / High Supply Elasticity



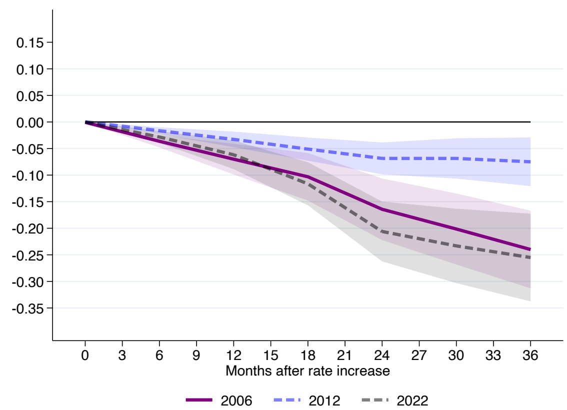

**(b)** High Debt Burden / High Supply Elasticity




**(c)** Low Debt Burden / Low Supply Elasticity




**(d)** High Debt Burden / Low Supply Elasticity




Notes: Figures present the conditional impulse response estimates from equation (9) based on a 100 basis point mortgage interest rate shock. High / low debt burden is the average of the top / bottom 33 percentiles of city-year observations respectively. Shading captures the pointwise 95% confidence intervals.

Sources: Freddie Mac; Fannie Mae; Blue Chip Financial Forecasters; Authors' analysis.

**Table A.1:** Effects on mortgage rates

| | |
|---|---|
| Dependent variable: | $r_{i,t+h} - r_{i,t-1}$ |
| Instrument for $\Delta$ Mortgage Rate: | BCFF forecast errors |

| | $h = 2$ | $h = 4$ | $h = 6$ | $h = 8$ | $h = 10$ | $h = 12$ |
|---|---|---|---|---|---|---|
| $\Delta$ Mortgage Rate | 1.35 | 1.45 | 1.07 | 0.53 | 0.33 | 0.19 |
| | (0.16) | (0.24) | (0.32) | (0.27) | (0.31) | (0.32) |
| Observations | 256 | 254 | 252 | 250 | 248 | 246 |
| $R^2$ | 0.479 | 0.355 | 0.232 | 0.193 | 0.174 | 0.182 |

Notes: The table shows the effect on mortgage rates of mortgage rate shocks. The dependent variable is the cumulative change in mortgage rates at horizon h = 2, 4, 6, 8, 10, and 12 months. Results are based on estimating cumulative mortgage rate changes as a function of its 13 lags, using the mortgage rate shock and its lag as IVs for the contemporaneous change. We also use 30 contemporaneous news surprises as controls. The dataset covers a time series over the period 2000:M1–2022:M8. Mortgage rates are modeled using Blue Chip Financial Forecasters (BCFF) 1-month-ahead forecast errors for mortgage rates as instruments. The heteroskedasticity-robust standard errors are reported in parentheses below the point estimates.
Sources: Fannie Mae; Blue Chip Financial Forecasters; Authors' analysis.

**Table A.2:** Alternative controls

| | Dependent variable: $p_{i,t+36} - p_{i,t-1}$ | | | |
|---|---|---|---|---|
| Instrument for $\Delta$ Mortgage Rate: | BCFF forecast errors | | | |
| Control set | standard | shock controls | local controls | period FEs |
| $\Delta$ Mortgage Rate | -0.54 | -0.47 | -0.45 | |
| | (0.19) | (0.19) | (0.19) | |
| $\times$ Share DTI>43 | -1.25 | -1.28 | -1.23 | -0.67 |
| | (0.24) | (0.23) | (0.24) | (0.21) |
| $\times$ DTI limit $\times$ 100 | 1.24 | 1.09 | 1.08 | |
| | (0.39) | (0.38) | (0.39) | |
| $\times$ Supply elasticity $\times$ 100 | 1.38 | 1.32 | 1.42 | 1.85 |
| | (0.74) | (0.71) | (0.74) | (0.49) |
| Observations | 52705 | 52705 | 52705 | 52705 |
| CBSAs | 253 | 253 | 253 | 253 |
| $R^2$ | 0.567 | 0.579 | 0.571 | 0.713 |

Notes: See table 1 notes for details on the sample, variable definitions, and estimator. The dependent variable is the cumulative 3-year change in log-house prices. The "shock controls" specification includes 30 contemporaneous macro news surprises and the lagged mortgage rate forecast error. The "local controls" specification includes 12 lags of both log wage earnings changes and employment changes at the CBSA level from the Bureau of Labor Statistics' Quarterly Census of Employment and Wages. The "Period FEs" specification includes a dummy variable for each time period in the sample; accordingly, the $\Delta$ mortgage rate and the $\Delta$ mortgage rate $\times$ DTI limit parameters are no longer identified.
Sources: Freddie Mac; Fannie Mae; Bureau of Labor Statistics; Blue Chip Financial Forecasters; Bloomberg; Authors' analysis.

# B Model derivations

$$
\begin{aligned}
H^* &= \frac{\tilde{z}^2}{2} Y(r-g)^\sigma P^\sigma + (1-\tilde{z})\theta Y(rP)^{-1} \\
&= \frac{(1-\lambda)^2}{2} Y(r-g)^\sigma P^\sigma + \lambda\theta Y(rP)^{-1} \\
&= Y(r-g)^\sigma P^\sigma \left(\frac{(1-\lambda)^2}{2} + \lambda\theta r^{-1}(r-g)^\sigma P^{-1-\sigma}\right) \\
&= Y(r-g)^\sigma P^\sigma \left(\frac{(1-\lambda)^2}{2} + \lambda(1-\lambda)\right) \\
&= \underbrace{\frac{Y(r-g)^\sigma P^\sigma}{2}}_{\text{All Borrower Channel}} - \underbrace{\frac{\lambda^2}{2} Y(r-g)^\sigma P^\sigma}_{\text{Constrained Borrower Channel}}
\end{aligned}
\tag{10}
$$

# C Constructing mortgage rate shocks

While the BCFF forecasts are for quarterly average values, we back out the implied monthly forecasts that are consistent with the weekly mortgage rate data that forecasters had access to when generating their forecasts. For example, when forecasters generate their forecasts at the end of the second month of each quarter, they have access to almost two full months of data for their forecast of the current quarter. Assuming forecasters used this information, we back out what the implicit forecast for the final month of the quarter must be in order to satisfy the forecast of the average mortgage rate over the full quarter. At the beginning of the quarter we assume that the forecast is equally distributed across all three months of the quarter. After the first month of the quarter, we back out what the average forecast over the next two months must be in order to satisfy the observed mortgage rate over the first month of the quarter and assume that it is equally distributed over these months. We also considered other assumptions on how to distribute the monthly forecasts, but the differences were negligible.

Below is a list of all macroeconomic news release surprises used to orthogonalize the forecast error series following Sherlund (2020).

**Table A.3:** Macroeconomic News Release Surprises

| | |
|---|---|
| Average Hourly Earnings | ISM Manufacturing |
| Building Permits | ISM Services |
| Capacity Utilization | MNI Chicago PMI |
| Change in Non-farm Payrolls | NAHB Housing Market Index |
| Conference Board Consumer Confidence | New Home Sales |
| CPI Ex Food and Energy | Pending Home Sales |
| Construction Spending | Personal Income |
| Consumer Credit | Philadelphia Fed Business Outlook |
| Durable Goods Orders | PPI Ex Food and Energy |
| Employment Cost Index | PPI |
| Existing Home Sales | Retail Sales Advance |
| Factory Orders | Retail Sales Ex. Autos |
| Real GDP Growth Annualized | S&P CoreLogic 20-City House Prices |
| Housing Starts | Trade Balance |
| Initial Jobless Claims | Unemployment Rate |

Notes: New release surprises are constructed by taking the difference between the actual release and the Bloomberg consensus forecast just prior to the release. All surprises are standardized to have a mean of 0 and a standard deviation of 1. All releases and forecasts are available since 2000 except for Building Permits (August 2002), NAHB Housing Market Index (April 2003), Pending Home Sales (June 2005), and S&P CoreLogic 20-City House Prices (June 2007).
Sources: Bloomberg; Authors' analysis.

# D Testing for DTI endogeneity

We analyze whether unexpected changes in mortgages rate affect the share of borrowers with high payment burdens. Table A.4 shows that after an initially small positive response, the effect is insignificant through 12-months and remains statistically indistinguishable from zero until 24 months. We interpret this as showing that, while there are no important effects on shorter horizons up through 18 months, $DTI43$ does respond significantly to unexpected mortgage rate shocks at horizons longer than 18 months. This illustrates that there is feedback between changes in mortgage rates and the share of borrowers with high debt payment burdens, especially at longer horizons, such that the lead exogeneity assumption is not satisfied.

**Table A.4:** Mortgage rates and $DTI43$

Dependent variable: $DTI43_{i,t+h} - DTI43_{i,t-1}$
Instrument for $\Delta$ Mortgage Rate: BCFF forecast errors

| | $h = 6$ | $h = 12$ | $h = 18$ | $h = 24$ | $h = 30$ | $h = 36$ |
|---|---|---|---|---|---|---|
| $\Delta$ Mortgage Rate | 2.44 | -0.41 | -2.41 | -8.51 | -8.19 | -12.32 |
| | (0.81) | (1.19) | (1.31) | (1.43) | (1.50) | (1.51) |
| Observations | 60492 | 58967 | 57440 | 55913 | 54387 | 52859 |
| CBSAs | 253 | 253 | 253 | 253 | 253 | 253 |
| $R^2$ | 0.418 | 0.398 | 0.452 | 0.491 | 0.536 | 0.581 |

Notes: See table 1 notes for details on the sample, variable definitions, and estimator. The dependent variable is the cumulative change in the city-specific share of Fannie Mae borrowers with back-end debt-to-income (DTI) ratios greater than 43 at horizon h = 6, 12, 18, 24, 30, and 36 months. $DTI43$ here is defined as its 12-month moving average. Results are based on estimating $DTI43_{i,t+h} = a_i + \beta_{1,h}\Delta r_t + \mathbf{\Gamma_h'W_{i,t}} + e_{i,t}$, which includes city fixed effects, and 13 lags of house prices, mortgage rates, $DTI43$, local wage earnings from the QCEW, and the change in the Fannie Mae DTI overlay as controls.

Sources: Freddie Mac; Fannie Mae; Bureau of Labor Statistics; Blue Chip Financial Forecasters; Authors' analysis.

# E Accounting for user costs

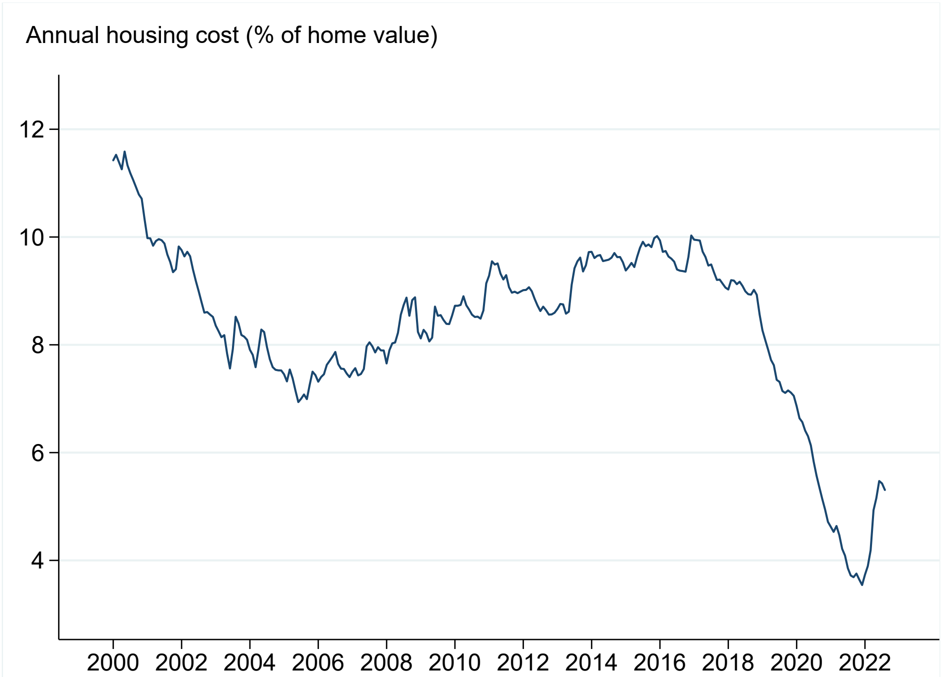
A fundamental prediction in the user cost literature (e.g Himmelberg et al., 2005) is that the semi-elasticity of house prices with respect to user costs is higher the closer the user cost is to zero. As discussed above, this result is implied by the dividend pricing formula $p = r/u$. Accordingly, it is possible the user cost and its arguments are important state-dependent controls for the effects of mortgage rate shocks. Variables in this class include the mortgage rate level, expectations, the user cost itself, and implied capitalization rates.

Table A.5 includes these additional state variable interactions and their lags over a series of four models. The first two include different expectations proxies, the 10-year (geometric) average appreciation rate, and the expected appreciation rate at the Census division level, measured using the Michigan Survey of Consumers question 47, "By about what percent per year do you expect prices of homes like yours in your community to go (up/down), on average, over the next 5 years or so?" None of these additional state interactions are significantly different from zero, and the original parameters are nearly the same as when the appreciation expectations variables are omitted.

The next two models incorporate the user cost and the capitalization rate. The user cost is calculated as: $u = discount + depreciation + taxes + insurance + r - g$. We assume the discount factor, depreciation, taxes, and insurance are equal to Himmelberg et al. (2005) and sum to 6% per year. The mortgage rate is the U.S. 30-year fixed rate mortgage rate, and the expected appreciation rate is at the city level and defined as the lagged 10-year appreciation rate. The resulting series is shown in figure A.7 for the employment-weighted U.S. average. Note that even though mortgage rates rose steeply between 2021 and 2023, user costs remain very low by historical standards. This is corroborated by the Michigan Survey data, which show house price expectations reached a series high (beginning in 2008) in 2024.[27] The capitalization rate is calculated using the city-level average ratio of the 1-bedroom annual rent divided by the 1-bedroom housing asset price. Neither the user cost nor the capitalization rate interaction variables are statistically significant, and all of the prior parameters of interest are mostly unchanged.

[27] See `https://data.sca.isr.umich.edu/data-archive/mine.php` for most recent data.

**Figure A.7:** Annual user cost of homeownership




Notes: User cost is calculated following Himmelberg et al. (2005) as $u = 6\% + r - g$, where $r$ is the 30-year fixed rate mortgage rate and $g$ is the lagged 10 year annual geometric average appreciation rate.

Sources: Freddie Mac; University of Michigan's Survey of Consumers; Authors' analysis.

**Table A.5:** User cost controls

Dependent variable: $p_{i,t+36} - p_{i,t-1}$
Instrument for $\Delta$ Mortgage Rate: BCFF forecast errors

| | Standard | Expectations (Lagged appr) | Expectations (Michigan) | User Cost | Cap Rate |
|---|---|---|---|---|---|
| $\Delta$ Mortgage Rate | -0.54 | -0.36 | -0.56 | -0.21 | -0.53 |
| | (0.19) | (0.19) | (0.19) | (0.22) | (0.19) |
| $\times$ Share DTI>43 | -1.25 | -1.25 | -1.30 | -1.23 | -1.27 |
| | (0.24) | (0.23) | (0.25) | (0.23) | (0.26) |
| $\times$ DTI limit $\times$ 100 | 1.24 | 0.88 | 1.25 | 0.96 | 1.24 |
| | (0.39) | (0.41) | (0.39) | (0.39) | (0.40) |
| $\times$ Supply elasticity $\times$ 100 | 1.38 | 1.82 | 1.53 | 2.13 | 1.35 |
| | (0.74) | (0.75) | (0.75) | (0.78) | (0.96) |
| $\times$ Prior 10 yr avg appr | | 1.21 | | | |
| | | (1.31) | | | |
| $\times$ Expected appr next 5 yr | | | 0.01 | | |
| | | | (0.02) | | |
| $\times$ User cost | | | | -2.18 | |
| | | | | (1.31) | |
| $\times$ Cap rate avg | | | | | 0.05 |
| | | | | | (0.22) |
| Observations | 52705 | 52705 | 52705 | 52705 | 48087 |
| CBSAs | 253 | 253 | 253 | 253 | 229 |
| $R^2$ | 0.567 | 0.570 | 0.568 | 0.568 | 0.577 |

Notes: See table 1 notes for details on the sample, variable definitions, and estimator. The dependent variable is the cumulative 3-year change in log-house prices. Column 2 uses the 10-year city-level lagged (geometric) average appreciation rate as a proxy for appreciation expectations. Column 3 uses the Census Division-level 5-year ahead appreciation expectation measure from the Michigan Survey of Consumers. Column 4 uses a measure of user costs constructed following Himmelberg et al. (2005). Column 5 uses a city-average capitalization rate for housing calculated using Zillow as the ratio of annual 1-bedroom rents to 1-bedroom home values.
Sources: Freddie Mac; Fannie Mae; Blue Chip Financial Forecasters; University of Michigan, Survey Research Center, Surveys of Consumers; Zillow; Authors' analysis.

# F Testing for supply elasticity asymmetry

Previous literature has established that the house price response to a demand shock should depend on the elasticity of housing supply. As the theory of Glaeser and Gyourko (2005) shows, the housing supply curve is "kinked" because housing can be constructed faster than it typically depreciates, resulting in a higher supply elasticity for upward shifts in demand. Under this theory, positive (contractionary) mortgage rate shocks should have larger (in magnitude) effects on house prices due to smaller supply effects. Expansionary shocks interact with the elasticity of housing supply in a city to mute the price effect via housing construction. Aastveit and Anundsen (2022) empirically verify these predictions using state-dependent local projections.

We offer some mixed evidence of this hypothesis using our updated model with a different sample. Table A.6 presents estimates from a model where the supply elasticity interaction with the mortgage rate shock is split into positive and negative shocks. In the pre-July 2008 sample, which corresponds to the underwriting regime with the 65 DTI limit and no overlays, expansionary (negative) mortgage rate shocks have larger effects that vary with the supply elasticity. This estimate is in line with the findings of Aastveit and Anundsen (2022). When the model is estimated over the full sample, the elasticity interaction effect approaches zero. However, there is some evidence that elasticities have fallen since the Great Recession (Aastveit et al., 2023) and we speculate this may be the cause of the null result. It seems possible that the static elasticity measure created by Saiz (2010) and used by much of the literature may be too rigid and time-varying elasticity measures are required. Overall, we suggest further investigation on this subject may be warranted, especially the development of time-varying estimates of the elasticity of housing supply, as the time-invariant measures which are used may be the source of the parameter instability.

**Table A.6:** Asymmetric effects

Dependent variable: $p_{i,t+36} - p_{i,t-1}$
Instrument for $\Delta$ Mortgage Rate: BCFF forecast errors

| | Standard | Supply elasticity asymmetry | Supply elasticity asymmetry |
|---|---|---|---|
| Sample: | Full | Pre-July 2008 | Full |
| $\Delta$ Mortgage Rate | -0.54 | 0.21 | -0.55 |
| | (0.19) | (0.09) | (0.19) |
| $\times$ Share DTI>43 | -1.25 | -1.12 | -1.24 |
| | (0.24) | (0.29) | (0.25) |
| $\times$ DTI limit $\times$ 100 | 1.24 | | 1.26 |
| | (0.39) | | (0.39) |
| $\times$ Supply elasticity $\times$ 100 | 1.38 | | |
| | (0.74) | | |
| (+) $\times$ Supply elasticity $\times$ 100 | | 3.10 | 1.36 |
| | | (1.33) | (1.09) |
| (-) $\times$ Supply elasticity $\times$ 100 | | 6.22 | 0.10 |
| | | (1.83) | (1.12) |
| Observations | 52705 | 18949 | 52705 |
| CBSAs | 253 | 253 | 253 |
| $R^2$ | 0.567 | 0.753 | 0.571 |

Notes: See table 1 notes for details on the sample, variable definitions, and estimator. The dependent variable is the cumulative 3-year change in log-house prices. Column 1 replicates the main results from table 1. Columns 2 and 3 consider positive and negative mortgage rate shocks interacted with the elasticity of housing supply and its 13 lags. The null of no asymmetry is not rejected in the model of columns 2 and 3 with p-values of 0.12 and 0.44, respectively.
Sources: Freddie Mac; Fannie Mae; Blue Chip Financial Forecasters; Authors' analysis.

# G Alternative standard errors

There are many ways to correct or adjust standard errors to account for unmodeled features of the data. The choice of a specific procedure depends on the underlying data generating process. A common approach is to cluster the standard errors. However, Abadie et al. (2023) show that clustered standard errors can be inflated unless clustering is done at the level at which the units are sampled or at which treatment is assigned. An alternative approach is to account for a specific temporal or spatial dependence structure in the residuals. We follow Aastveit and Anundsen (2022) in using Conley (1999) standard errors that are robust to both spatial and autocorrelations. While Aastveit and Anundsen (2022) chose a 100 mile cutoff to capture typical commuting zones, we take a more conservative approach and use to 1000 km cutoff to account for larger distances between MSAs in the southwest (e.g. Phoenix to Las Vegas is nearly 500km) and allow for larger commuting zones which are more prevalent since the pandemic and spread of remote work arrangements; see Howard et al. (2023).

Table A.7 shows that our choice of using SpHAC standard errors with a bandwidth of 1000km is more conservative than all those considered except for those produced using the (two-way) clustering formula of Thompson (2011) and Cameron et al. (2011). Importantly, these standard errors are 3x-4x those of the basic standard error formulas with or without correcting for heteroskedasticity (White, 1980) and the SpHAC estimator with low bandwidth. While a bandwidth of 100 miles may be appropriate in dense countries or regions or when the sampled units are close by, for relatively sparse samples in more spread-out countries, such as the U.S., Canada, or Brazil, it is important to choose a bandwidth that reflects the geographic distribution of the cities in the sample to conduct proper inference. This is consistent with the approach in Abadie et al. (2023) where the level of clustering should be consistent with how the data are sampled.

**Table A.7:** Alternative standard errors

| | |
|---|---|
| Dependent variable: | $p_{i,t+36} - p_{i,t-1}$ |
| Instrument for $\Delta$ Mortgage Rate: | BCFF forecast errors |

| | Parameter | Basic | White ("robust") | SpHAC 160km | SpHAC 1000km | Cluster (i,t) |
|---|---|---|---|---|---|---|
| $\Delta$ Mortgage Rate | -0.54 | (0.05) | (0.05) | (0.06) | (0.19) | (0.48) |
| $\times$ Share DTI>43 | -1.25 | (0.06) | (0.07) | (0.09) | (0.24) | (0.57) |
| $\times$ DTI limit $\times$ 100 | 1.24 | (0.10) | (0.10) | (0.14) | (0.39) | (0.99) |
| $\times$ Supply elasticity $\times$ 100 | 1.38 | (0.31) | (0.29) | (0.36) | (0.74) | (1.35) |
| Observations | 52705 | | | | | |
| CBSAs | 253 | | | | | |
| $R^2$ | 0.567 | | | | | |

Notes: See table 1 notes for details on the sample, variable definitions, and estimator. The dependent variable is the cumulative 3-year change in log-house prices. "Basic" standard errors use the classic formula assuming homoskedasticity. "White" standard errors are from White (1980), are heteroskedasticity-robust, and implemented in STATA using the "ivreg2" estimator with the "robust" option. The "SpHAC" standard errors are based on Conley (1999) and are robust to both spatial correlation and autocorrelation. STATA code was developed by Hsiang (2010) and Aastveit and Anundsen (2022) and updated by Foreman (2020) for use with instrumental variables. CBSA centroids are used for distances, with the cutoff distance for the spatial correlation at 160 kilometers as in Aastveit and Anundsen (2022), and then a more conservative 1,000 kilometers. The Bartlett kernel that is used to weigh the spatial correlations decays linearly with distance in all directions. "Cluster (i,t)" standard errors use the Thompson (2011) and Cameron et al. (2011) formula, and are implemented by using the ivreghdfe estimator in STATA with the "cluster(i t)" option. The standard errors are reported in parentheses to the right of the point estimates.
Sources: Freddie Mac; Fannie Mae; Blue Chip Financial Forecasters; Authors' analysis.

# H Alternative credit risk state variables

**Table A.8:** Alternative credit risk state variables

Dependent variable: $p_{i,t+36} - p_{i,t-1}$
Instrument for Δ Mortgage Rate: BCFF forecast errors

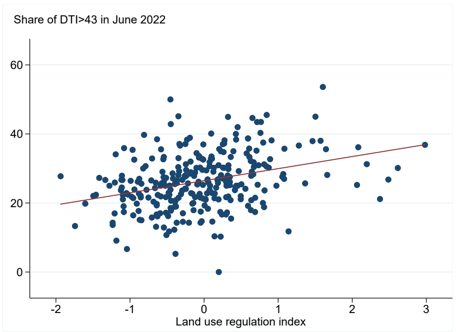
| | | — % *LTV* > 90 — | | | % Credit Score < 660 | |
|---|---|---|---|---|---|---|
| | Standard | FNM | FNM+FRE | All | FNM+FRE | All |
| Δ Mortgage Rate | -0.54 | -0.35 | -0.45 | -0.60 | -0.77 | -0.58 |
| | (0.19) | (0.17) | (0.18) | (0.17) | (0.19) | (0.18) |
| × Share DTI>43 | -1.25 | -1.03 | -1.14 | -1.05 | -1.29 | -1.12 |
| | (0.24) | (0.22) | (0.24) | (0.22) | (0.25) | (0.23) |
| × DTI limit × 100 | 1.24 | 0.80 | 1.04 | 1.06 | 1.73 | 1.41 |
| | (0.39) | (0.33) | (0.38) | (0.34) | (0.40) | (0.39) |
| × Supply elasticity × 100 | 1.38 | 0.95 | 1.22 | 0.55 | 1.78 | 2.29 |
| | (0.74) | (0.61) | (0.78) | (0.63) | (0.90) | (0.83) |
| × Share LTV>90 | | 0.34 | 0.09 | 0.31 | | |
| | | (0.21) | (0.10) | (0.09) | | |
| × Credit Score<660 | | | | | -0.51 | -0.49 |
| | | | | | (0.15) | (0.13) |
| Observations | 52705 | 52705 | 49791 | 52642 | 49791 | 52642 |
| CBSAs | 253 | 253 | 253 | 253 | 253 | 253 |
| $R^2$ | 0.567 | 0.629 | 0.596 | 0.620 | 0.578 | 0.573 |

Notes: See notes in table 1 of the main paper for details on the sample, variable definitions, and estimator. The dependent variable is the cumulative 3-year change in log-house prices. Columns 2-7 add additional dynamic state variables, including interactions, leads, and lags in the same manner as the Share DTI variable. Column 2 uses the share of borrowers in the Fannie Mae public use file with combined LTV>90. Columns 4 and 5 uses the same measure in the NMDB, with the full GSE sample and the universe of all loans, respectively. Columns 6 and 7 use the share of borrowers with Vantage scores less than 660.
Sources: Freddie Mac; Fannie Mae; Blue Chip Financial Forecasters; National Mortgage Database; Authors' analysis.

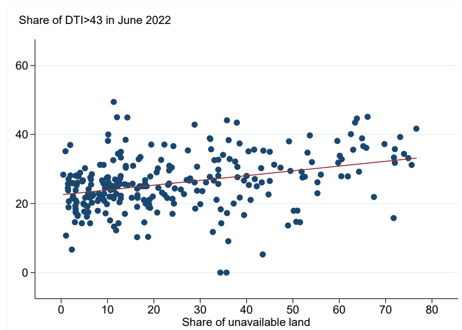
# I Alternative supply elasticity state variables

**Figure A.8:** High ($> 43$) DTIs and elasticity measures, full set

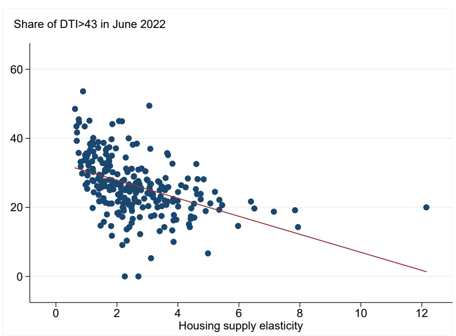
**(a)** Land use regulation (Gyourko et al., 2021)
$DTI43 = 25.4(0.5) + 3.5(0.6) \times WRLURI$
$N = 288$; $R^2 = 0.11$



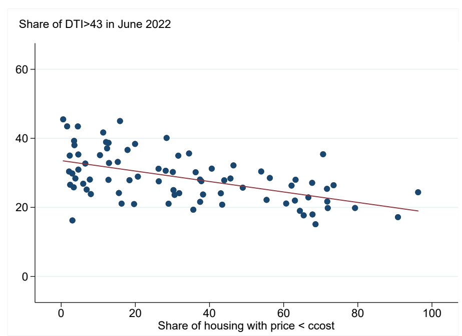

**(b)** Unavailable land (Saiz, 2010)
$DTI43 = 22.5(0.6) + 0.14(0.02) \times UNAVAIL$
$N = 264$; $R^2 = 0.12$



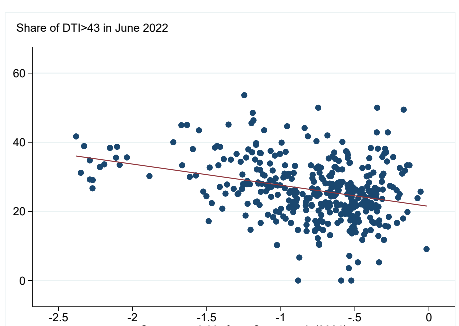

**(c)** Elasticity of housing supply (Saiz, 2010)
$DTI43 = 33.1(1.2) - 2.6(0.5) \times \eta$
$N = 253$; $R^2 = 0.20$




**(d)** Urban decline (Glaeser and Gyourko, 2005)
$DTI43 = 33.5(1.23) - 0.15(0.03) \times q$
$N = 80$; $R^2 = 0.29$




**(e)** Elasticity IV (Guren et al., 2021)
$DTI43 = 21.4(0.85) - 6.1(0.84) \times \gamma$
$N = 378$; $R^2 = 0.10$




Sources: Fannie Mae; Saiz (2010); Glaeser and Gyourko (2005); Gyourko et al. (2021); Guren et al. (2021); Authors' analysis.

**Table A.9:** Alternative supply elasticity state variables

Dependent variable: $p_{i,t+36} - p_{i,t-1}$
Instrument for Δ Mortgage Rate: BCFF forecast errors

| | Supply Elasticity | Urban Decline | Unavailable Land | Land use Regulation | Sensitivity IV |
|---|---|---|---|---|---|
| Δ Mortgage Rate | -0.50 | -0.50 | -0.52 | -0.54 | -0.46 |
| | (0.19) | (0.21) | (0.19) | (0.19) | (0.20) |
| × Share DTI>43 (MA[12]) | -1.25 | -1.27 | -1.26 | -1.32 | -1.15 |
| | (0.24) | (0.27) | (0.24) | (0.25) | (0.24) |
| × DTI limit × 100 | 1.24 | 1.25 | 1.27 | 1.34 | 1.13 |
| | (0.39) | (0.43) | (0.38) | (0.38) | (0.40) |
| × Elasticity (column) × 100 | 1.99 | 0.95 | 1.85 | 1.38 | 4.11 |
| | (1.07) | (1.36) | (1.05) | (0.84) | (1.87) |
| Observations | 52705 | 15825 | 50760 | 43739 | 52596 |
| CBSAs | 253 | 75 | 242 | 210 | 251 |
| $R^2$ | 0.567 | 0.601 | 0.569 | 0.566 | 0.579 |

Notes: See notes in table 1 of the main paper for details on the sample, variable definitions, and estimator. The dependent variable is the cumulative 3-year change in log-house prices. The columns use alternative housing supply elasticity variables as static, state-dependent interaction variables. These are each standardized and signed such that a higher value indicates higher elasticity of housing supply. Column 1 uses the standardized version of the Saiz (2010) elasticity variable. Column 2 uses the urban decline variable from Glaeser and Gyourko (2005). Column 3 uses Saiz (2010) unavailable land measure. Column 4 uses the Wharton Land Use Regulatory Index (WRLURI) from Gyourko et al. (2021). Column 5 uses the elasticity instrumental variable derived from house price sensitivities to regional house price cycles from Guren et al. (2021).
Sources: Freddie Mac; Fannie Mae; Blue Chip Financial Forecasters; Saiz (2010); Glaeser and Gyourko (2005); Gyourko et al. (2021); Guren et al. (2021); Authors' analysis.