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November 2022

Working Paper 22-04

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Please address correspondence to William Larson (william.larson@fhfa.gov). Thanks to Justin Contat, Len Costa, Tom Daula, Will Doerner, Tara Sinclair, and seminar participants at the Federal Forecasters annual conference and the Federal Housing Finance Agency for comments, questions, and encouragement.

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Abstract

This research examines the effects of mortgage interest rates on house prices in the 100 largest U.S. cities, with appreciation driven by both short-run dynamics and convergence towards long-run economic fundamentals. The nature of the long-run equilibrium depends on the elasticity of housing supply, and the speed of adjustment to this long-run equilibrium depends on the degree to which borrowers are near monthly debt service payment constraints. Accordingly, the pass-through of mortgage interest rates to house prices is location and time-varying. This has implications for our understanding of monetary policy transmission, systemic risk, and the role of household finances in the macroeconomy.

Keywords: Asset Pricing · Household Finance · House Price Bubbles

JEL Classification: G21, G51, E43, R30, C23.

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1 Introduction

Recent fluctuations in mortgage interest rates have called into question their effects on housing asset prices. The primary channel linking the two in the existing literature is through the "user cost" of housing, that is, the net flow cost of a unit of housing (e.g. Hendershott and Slemrod, 1982; Gallin, 2008). As the theory goes, in equilibrium, if interest rates rise, asset prices should fall, holding rental prices constant. However, this equilibrium correction process can take a number of years, as prices and rents can be slow to adjust to changing market fundamentals.

Interest rates may serve another role by affecting the speed by which prices *adjust* to long-run fundamentals. In addition to linking rents and asset prices, the mortgage interest rate affects the bindingness of debt service constraints, also called payment constraints (Greenwald, 2018).[1] Mechanically, the mortgage interest rate determines the maximum loan amount a borrower can afford under a fixed monthly payment.[2] Accordingly, a constrained borrower cannot increase housing expenditures as an unconstrained borrower would choose given the simultaneous rise in user costs.[3] It follows that if an area includes many such constrained borrowers, the rate of equilibrium correction of house prices may be higher. On the other hand, if an area contains few such borrowers, prices may adjust more slowly. In sum, interest rates may affect not only the long-run equilibrium asset price of housing, but also the speed of adjustment to the new long-run equilibrium by affecting the bindingness of borrowing constraints.

This paper quantifies the effect of mortgage interest rate changes on house prices, considering effects to both long-run fundamental values and speeds of adjustment. Building on

[1] On the supply side, borrowing constraints can be discontinuities introduced by regulation, such as the Qualified Mortgage (QM) Rule in the United States, which places limits on borrowing to 43% debt-service to income (DTI) each month in order for a loan to qualify. See `https://www.govinfo.gov/app/details/STATUTE-124/STATUTE-124-Pg1376` and `https://www.federalregister.gov/documents/2013/01/30/2013-00736/ability-to-repay-and-qualified-mortgage-standards-under-the-truth-in-lending-act-regulation-z` for more details on different vintages of QM rules. Even without hard caps, extreme DTIs typically require higher mortgage interest rates to compensate for default risk (Anenberg et al., 2019). Generally speaking, at high DTI levels, the more costly it is to adjust the DTI further upward.

[2] For example, assume an interest-only loan and a \$2000 monthly payment. The maximum loan amount is then the perpetuity $1/r \times 2000 \times 12$, where for $r = 3\%$, the maximum loan amount is \$800,000; for $r = 4\%$, the maximum loan amount is \$600,000; and so on.

[3] Typical estimates of the own-price elasticity of demand for housing are -0.5 to -0.8 (Albouy et al., 2016). An elasticity of beyond -1.0 would be required for borrowing constraints not to be binding.

McQuinn and O'Reilly (2008) and Oikarinen et al. (2018), I model house prices, incomes, borrowing constraints, and mortgage interest rates in a cointegration framework, with house prices driven by both short-run dynamics and convergence towards long-run economic fundamentals. After testing for the existence of this cointegrating relation, I show the nature of a city's long-run equilibrium depends on the elasticity of housing supply, and the speed of adjustment to this long-run equilibrium depends on the degree to which borrowers are near debt service-to-income (DTI) constraints.

Estimates from individual cities suggest long-run elasticities of house prices with respect to interest rates between about -0.2 to -0.8. When the city-level estimates are fit to the Wharton Land Use Regulatory Index of Gyourko et al. (2021), the most lightly regulated cities have an average elasticity of -0.3 and the most tightly regulated cities have an average elasticity of -0.6. This elasticity differential arises because demand changes induce greater quantity responses in cities facing low constraints to development, with interest rates putting less pressure on prices.

Payment constraints and the elasticity of housing supply are highly correlated across cities and load multiplicatively onto the short-run interest rate elasticity, creating substantial heterogeneity in the dynamic effects of mortgage interest rate changes on house prices. The largest short-run house price elasticities are found in areas with both housing supply constraints and DTI-constrained borrowers. For example, in a hypothetical supply-elastic, payment-unconstrained city with 3% mortgage interest rates, the cumulative 3-year effect of a permanent 0.25% (25 basis point) increase in interest rates is about -1.46%. On the other hand, in a city facing both housing supply and mortgage credit constraints, the cumulative effect on house prices is almost triple at -4.32%.

The functional form motivated by theory suggests nonlinearity in the effect of interest rate changes, with lower base levels having larger effects than higher base levels for the same percentage point change in rates. At the median supply elasticity and level of constrained borrowers, a change in rates from 3% to 3.25% gives gives a cumulative -2.51% (partial) house price change over 3 years, versus a 6% to 6.25% change giving a -1.28% change over the same period.

Finally, there is some evidence of asymmetric effects. When house prices are below their long-run fundamental value, interest rate changes do not affect convergence speeds, with prices converging at a flat 5% of the degree of disequilibrium per quarter. When house prices are above fundamental values, convergence does not occur unless DTIs are high. Only if the share of borrowers in a city with a back-end $DTI \geq 43$ is 40% (the median rate across cities in 2008 and the 95th percentile in 2021) or more does convergence approach 5% per quarter. The implication of this result is that house prices bubbles only seem to revert to fundamentals once borrowers begin to face payment constraints, which are affected by changes to interest rates, mortgage credit supply, or incomes. On the other hand, in recovery periods, house prices will slowly but steadily recover their value over time as long as economic fundamentals are strong.

This research contributes to at least three important literatures. The first concerns the effects of mortgage interest rates on house prices. There are typically two approaches to modeling this relation, either directly, or embedded within a user-cost framework. Direct estimates have focused on cross-country studies (e.g. Muellbauer and Murphy, 1997; Shi et al., 2014) and show country-specific effects of interest rates on house prices. Perhaps surprisingly, there is little direct evidence in the literature of effects of mortgage interest rates on house prices in the United States, with key papers finding no effect (e.g. Holly et al., 2010; Oikarinen et al., 2018). Maclennan et al. (1998) argue that institutions affect pass-through of interest rates to house prices, suggesting that some factor unique to the U.S. might diminish the effects. Other studies, such as McQuinn and O'Reilly (2008) suggest that because house prices have long cycles and interest rates fluctuate at high frequency, it is simply statistically difficult to estimate a precise effect if the true effect were small. Recently, Gorea et al. (2022) show using real estate listings data that monetary policy shocks affect house prices with little lag by affecting list prices. When embedded in user-costs, Capozza et al. (2002), Gallin (2008), and others have shown interest rates to affect house prices, but only insofar as they affect the long-run fundamental house price level.

The second strand is the growing literature on interest rate pass through on the real economy and heterogeneity across regions. Concerning mortgages, 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 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.

The third investigates the effects of household finance circumstances and decisions on the macroeconomy. Because payment constraints consider all household debts, there is a direct effect of student loans and other substantial debt classes on interest rate pass-through to the housing market. Auto loans, credit card debt, and student loan debt therefore all contribute to monetary policy transmission to the housing market and beyond. For instance, Cloyne et al. (2020) shows that in the UK, households with high levels of mortgage debt respond to interest rate changes with changing consumption patterns. There is also the large literature linking housing to the macroeconomy, including Mian et al. (2013) who show wealth shocks brought about by house price declines led to reduced consumption in the Great Recession, and Iacoviello (2005), who argues that monetary policy affects homeowners' balance sheets and can affect consumption through a housing wealth channel. Recently, Greenwald (2018) models mortgage interest rates and housing within a DSGE model of the U.S. economy, finding that payment-to-income ratios affect 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. Finally, this research points to the need for heterogeneous agent models of the macroeconomy (e.g. Mitman, 2016; Debortoli and Galí, 2017; Kaplan et al., 2018) in order to understand how a small number of marginal agents may have an outsized effect on market price dynamics and other behaviors that are relevant in aggregate.

2 Conceptual Framework

Housing markets in U.S. cities tend to be driven both by local characteristics, yet subject to national cycles through propagation of macroneconomic shocks. Demand factors are commonly though to drive short-run price fluctuations, with supply playing an important role the longer the time horizon. In many locations, strong real estate price cycles are common, while in others, dynamics are weaker. The model in this section attempts to capture the fundamental price of housing in a particular city, that is, the long-run, location-specific equilibrium to which prices will tend toward. This equilibrium is potentially unique to a particular location in a particular time period, continuously evolving with drivers of the fundamental price. In the literature, some housing market fundamentals include the housing to population ratio, rents, incomes, user costs (including interest rates, property taxes, insurance, and expected appreciation), credit availability, and other demand and supply shifters (e.g. Muellbauer and Murphy, 1997). A key concept in this section is the role of the marginal borrower, and how this borrower acts to set the market price (Duca et al., 2011). This household typically borrows near income and leverage constraints, and its presence in the market tends to affect the equilibrium price.

The starting point for the model in this section is McQuinn and O'Reilly (2008). Its focus is bringing borrowing constraints, interest rates, and incomes into a simple model of housing supply and demand. The model represents the latent steady-state relation between the variables to which actual variables will tend toward. The model's purpose is not to model perfectly the relation between all of the myraid costs and benefits of homeownership that are certain to vary across individuals, cities, locations, and time periods. Rather, it is meant to motivate the link between household borrowing and the price of housing that is modeled empirically in later sections. For additional simplicity, assume all mortgages are infinitely lived, and housing is financed exclusively through fixed-rate interest-only mortgages.[4] All other arguments in the user cost function, such as taxes, depreciation, and expected appreciation per unit of housing, are assumed to be zero for simplicity.

The maximum amount a household can borrow B at time t is defined by the perpetuity below, where $\bar{K}$ is the maximum debt service fraction of income that can be spent on housing, Y is income, and R is the mortgage interest rate, all at time t.

$$B_t = \sum_{j=1}^{\infty} \bar{K}_t Y_t (1 + R_t)^{-j} \tag{1}$$

After discounting the infinite sum of interest payments, the maximum loan amount can be expressed as the following product.[5]

$$B_t = \bar{K}_t \frac{Y_t}{R_t} \tag{2}$$

Assuming this marginal borrower drives the market price, the maximum loan amount can

[4]This implies loans have a 100% loan-to-value (LTV) ratio. The marginal borrower in an area typically is constrained by one or both of LTV or DTI. As Greenwald (2018) shows, LTV constraints tend not to affect the price of housing unless DTI is also constrained. I leave consideration of LTVs and their empirical interactions with DTI constraints to future research.

[5]For a numerical illustration, consider a maximum debt-service to income ratio of 40%, an income of \$100,000, and an interest rate of 4%. The maximum loan amount is \$1,000,000, corresponding to \$3,333 per month.

then be embedded into a simple downward-sloping (inverted) demand curve, where S is housing supply and $1/\mu$ is the own-price elasticity of demand for housing. Note this is almost identical to the inverted demand equation for house prices from Duca et al. (2010).[6]

$$P_t^D = B_t S_t^{-\mu} \tag{3}$$

The supply curve is expressed as follows, where $1/\phi$ is the own-price elasticity of housing supply.

$$P_t^S = S_t^{\phi} \tag{4}$$

Substituting and taking logs (lowercase) yields the equilibrium price as a function of the supply and demand elasticities and the maximum loan amount.

$$p_t = \frac{\phi}{\phi+\mu} b_t = \frac{\phi}{\phi+\mu}(\bar{k}_t + y_t - r_t) \tag{5}$$

Note that in the short run, it is possible to assume ϕ approaches infinity, leading price changes to be exclusively demand-driven. In the longer run, supply forces shape the responsiveness of prices to changes in the economic fundamentals in the model— borrowing constraints, incomes, and interest rates—with the effects of interest rates decreasing with the elasticity of housing supply.

The model in this section gives a simple relation between house prices and economic fundamentals, including mortgage interest rates, borrowing constraints, and incomes. This is termed the fundamental or long-run price of housing for the remainder of the paper. This long-run price varies by time and location as fundamentals change. There is no guarantee an area will ever converge to this long-run price, as fundamentals may change faster than observed prices. In this sense, the effects of mortgage rates on house prices require modeling both the continuously changing latent long-run relation between house prices and fundamentals, and the determinants of short-run fluctuations of the price of housing.

[6] The equation is: $\ln P = (\beta \ln Y - \alpha \ln(R + \delta + \tau - E[\dot{P}] + \theta z - \ln S)/\alpha$. They key difference is equation 3 omits the term $\delta + \tau - E[\dot{P}]$ and z, which include depreciation (δ), taxes (τ), expected appreciation ($E[\dot{P}]$), and other factors (z).

3 Cointegration and House Prices

House prices exhibit a high degree of momentum (Case and Shiller, 1989), while at the same time, being driven by fundamental microeconomic principles of producer and consumer theory (Muellbauer and Murphy, 1997). Accordingly, the cointegration and equilibrium correction framework of Engle and Granger (1987) is a natural fit for those seeking to model house price time series. In the cointegration literature, short-run dynamics are driven both by recent fluctuations in determinants and the level of deviation in the level of the series from its long-run equilibrium value.

Cointegration analysis proceeds in two steps following Engle and Granger (1987). To summarize briefly, the first step involves specifying a long-run equlibrium model of nonstationary I(1) variables in levels which share common stochastic trends. The operating hypothesis is that a linear combination of these I(1) variables is I(0) and stationary, also called "cointegrated". The second step takes a short-run dynamic model of the same variables from the first stage, first-differenced in order to make them I(0), and includes the residuals from this first-stage model as an additional term representing a measure of disequilibrium from a fundamental valuation. The parameter on the disequilibrium measure, α, gives the speed of adjustment towards this equilibrium (were it to exist). Hypothesis tests can then be conducted to determine whether the variables in the first stage are cointegrated.

There is no shortage of cointegration analysis involving house prices in the literature.[7] The major empirical challenge lies in the length of housing cycles, which can last over 15 years (peak to peak), and the paucity of long time series available, most of which start in 1990 or later, though there are some exceptions. While some have found house prices to be cointegrated with economic fundamentals such as rents (e.g Gallin, 2008), others have had mixed success establishing the existence of a long-run equilibrium involving incomes (e.g. Malpezzi, 1999; Gallin, 2006). Some researchers have sought to exploit the panel dimension to overcome the small number of cycles observed in individual locations (e.g. Holly et al., 2010; Oikarinen et al., 2018). Panel test statistics typically require accounting for cross-sectional dependence, as many locations are correlated with others within the panel.

[7] A Google Scholar search of {"cointegration" and "house prices"} returns 7,660 results. In fact, one of the seminal papers on cross-sectional dependence in panel models, written by Holly et al. (2010), uses U.S. regional house prices as its application.

It is, however, challenging to model interest rates in cointegrating (i.e. long-run) regressions. Because house prices tend to move in long, broad cycles, and interest rates are substantially more volatile, it has been necessary to use theoretically valid restrictions to identify an effect. For instance, Oikarinen et al. (2018) model interest rates along with incomes in a cointegration framework using data on U.S. cities, but find no effect of interest rates on house prices, neither in the short-run nor long-run portions of the model. The solution of McQuinn and O'Reilly (2008) is to augment incomes with interest rates in an "ability to pay" framework, which was the basis for the model in Section 2. From this launch point, I begin my cointegration analysis of house prices.

The simple model in Section 2 suggests the presence of a common trend between p and b and thus that these two series are cointegrated. Accordingly, I hypothesize and specify a cointegrating regression between house prices, incomes, borrowing constraints, and interest rates following equation 5 which reflects a period and location-specific fundamental value of housing. I assume the elasticity of supply is location-specific but time-invariant, suggesting different β_1s across locations. Borrowing constraints and interest rates are set at the national level and are invariant with respect to location, giving $b_{it} = k_t + y_{it} - r_t$, and

$$p_{it} = \beta_{i0} + \beta_{i1} b_t + u_{it} \tag{6}$$

with the long-run elasticity with respect to income and borrowing constraints given by β_{i1}, with respect to interest rates of $-\beta_{i1}$, and the elasticity of housing supply given by $\sigma_i = \frac{1}{\phi_i} = \frac{1-\beta_{i1}}{\mu\beta_{i1}}$, assuming a known elasticity of demand (Harter-Dreiman, 2004). Note that this parameterization implicitly assumes incomes, interest rates, and borrowing constraints all load the same onto the fundamental price of housing. The measure of disequilibrium is then $\hat{u}_{it} = p_{it} - \hat{\beta}_{i0} - \hat{\beta}_{i1} b_t$.

Estimation of equation 6 can be performed using equation-by-equation OLS without augmentation (e.g. Pesaran and Smith, 1995). It is common to model u using a factor structure to account for cross-sectional dependence, $u_{it} = \boldsymbol{\lambda}_i' \boldsymbol{F}_t + v_{it}$. However, Engle and Granger (1987) note that in cointegrating regressions, because both p and b are I(1) and cointegrated and u is I(0), endogeneity bias due to correlation between b and u is dwarfed by the variance of b.[8] Despite this result, researchers often attempt to control for $\mathbf{F}$ on the right-hand side of the regression, with two of the most common being the inclusion of the mean of p and b, (Holly et al., 2010) or augmentation with a term representing a common dynamic process (Teal and Eberhardt, 2010).

The equilibrium house price represented by the economic fundamentals in equation 6 is just one possible formulation. Alternative specifications with other variables or parameter restrictions are also considered, including different interest rates and a 30-year amortization term. After performing some basic time series tests of the component series, there are two key questions which are answered in turn. First, does the cointegrating relation in equation 6 exist, and second, does this equation adequately specify the long-run relation compared to alternatives?

3.1 Time series tests

Having estimated the long-run fundamental house price, it is necessary to determine whether house prices do, in fact, tend toward it. Standard tests involve specifying a short-run dynamic model of house prices, including the disequilibrium term from equation 6. Assume house prices follow a bivariate vector equilibrium correction model, estimated city-by-city. In this model, $\mathbf{x} = [p\ b]'$ is modeled as a function of lagged changes in house prices, lagged changes in the maximum loan amount, and the state of disequilibrium between the house price level and its fundamental value. With vectors in bold and omitting city subscripts,

$$\Delta \mathbf{x}_t = \mathbf{a} + \boldsymbol{\alpha} \hat{u}_t + \sum_{j=1}^{J} \mathbf{d}_j \Delta \mathbf{x}'_{t-j} + \mathbf{e}_t \tag{7}$$

Tests for cointegration can be residual-based or parameter-based. The standard Engle-Granger approach is to test for stationarity of $\hat{u}$, that is, the measure of disequilibrium. Were disequilibrium to persist forever, it would suggest that the variables in the cointegrating regression do not share a common stochastic trend and there is no linear combination that is

[8] Such endogeneity could arise if house prices and wages are simultaneously determined, e.g. through a high fraction of workers in homebuilding industries, and if house prices influence payment constraints such as the case in the early Great Recession period when underwriting noticeably tightened in response to declining house prices.

I(0).[9] This approach has received some criticism from Kremers et al. (1992) and others, who argue that this residual-based test implicitly restricts short-run dynamic relations between elements of $\mathbf{x}$ and the long-run cointegrating relation. Instead, a test with higher power is the null hypothesis that $\boldsymbol{\alpha} = \mathbf{0}$. This family of tests assesses whether the system $\mathbf{x}$ is tends towards equilibrium based on $\hat{u}$. This occurs only if some $\alpha < 0$. Banerjee et al. (1998) breaks apart the equilibrium correction term from equation 7 and tests directly the parameters on p_{t-1}, which are the same αs as equation 7 and includes α in the house price equation. Similarly, the test of Johansen (1995) does not impose a common factor restriction (see Lütkepohl et al., 1999). Accordingly, the cointegration tests of Johansen (1995) and Banerjee et al. (1998) are preferred.

3.2 Panel tests

There are also panel cointegration tests. Rather than estimate equation 7 city-by-city, it is possible to estimate a similar model of short-run house price dynamics in a panel regression in order to gain power. When T is large, Nickell (1981) bias is assumed to be small and ignored; estimators are more complex when T is small. As was the case with the cointegrating regression, the error structure has been the focus of much recent research, with factor-augmented specifications now common. Below is the standard dynamic model used to perform panel cointegration tests,

$$\Delta \mathbf{x}_{it} = \mathbf{a}_i + \boldsymbol{\alpha} \hat{u}_{it} + \sum_{j=1}^{J} \mathbf{d}_j \Delta \mathbf{x}'_{it-j} + \mathbf{e}_{it} \tag{8}$$

where $\mathbf{e}_{it} = \boldsymbol{\lambda}'_i \boldsymbol{F}_t + \boldsymbol{\epsilon}_{it}$. Typically, house price changes exhibit cross-sectional dependence. Westerlund (2007) derives four tests based on the Banerjee et al. (1998) method of testing for cointegration, that is, direct tests of $\boldsymbol{\alpha} = \mathbf{0}$. Rather than controlling for $\boldsymbol{\lambda}'_i \boldsymbol{F}_t$, critical values are based on bootstrapped distributions that preserve the correlated structure of the data. The first two test the null hypothesis of no cointegration for the panel as a whole, while the other test the null that at least one cross-sectional unit is cointegrated.

[9] This flavor of test is employed by Gallin (2006) who shows a failure to reject the null hypothesis of no cointegration between house prices and incomes.

4 Data Overview

The base dataset consists of publicly-available house price indices produced by the Federal Housing Finance Agency (FHFA) for the largest 100 cities at a quarterly frequency. This is merged with proprietary data on borrower and loan characteristics for Enterprise (Fannie Mae and Freddie Mac) loans aggregated to the same geographies and time periods. Finally, these series are supplemented with publicly available measures of interest rates and other macroeconomic indicators.[10] The sample used in analysis is a balanced panel of these 100 cities at a quarterly frequency between 1996Q1 and 2021Q4.

4.1 House prices

The source of house prices, P, is the "expanded-data" repeat-sales house price indices produced by the FHFA.[11] This index takes purchase transactions from the Enterprises, the Federal Housing Administration (FHA), and county recorder files (from CoreLogic) to construct quarterly house price indices from 1990Q1 through 2022Q2. To ensure sufficient transactions counts, this index database is limited to the largest 100 cities. The definition of a "city" is based on Core-Based Statistical Areas (CBSA, 2020 definitions), and Metropolitan Divisions (CBSADs) where available.

4.2 Borrower and loan characteristics

Borrower and loan aggregates are calculated using proprietary Enterprise data on first-lien home purchase loans originated between 1996Q1 and 2021Q4. Loans across both Enterprises are pooled within each city-quarter cell to calculate aggregates. The back-end DTI (the sum of all debt servicing costs divided by income) is used as the debt service payment constraint measure. In years prior to 2009, an increasing fraction of DTIs are missing in the database and are imputed based on the procedure found in Davis et al. (2022).

The maximum loan amount measure, B_{it}, requires a value of credit standards for a particular

[10] 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. In the present research, price levels either appear on both sides of equations (thus cancelling) or are absorbed within fixed effects. There is a preference for modeling nominal variables, however. 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. Accordingly, all variables are modeled as nominal.

[11] This database can be found at the following static URL: `https://www.fhfa.gov/DataTools/Downloads/Documents/HPI/HPI_PO_metro.txt`. The index used is the seasonally-adjusted series, `index_sa`.

time period, $\bar{K}_t$. The primary issue is that credit demand is non-constant across locations, so an average or threshold measure for a particular location is insufficient. I take the average DTI in the 95% percentile city as a measure of the frontier DTI to be used in the maximum loan amount calculation. Of course there is no true "maximum" DTI, as DTIs can rise if compensated with higher interest rates or months of reserves. The credit availability frontier (Anenberg et al., 2019) is also determined by credit scores and other characteristics. However, this measure should suffice as an index to track general trends in debt service payment constraints in the U.S. over time.

In addition to this national measure of maximum DTI, I also calculate DTI metrics for each city-quarter cell, including the average DTI and the fraction of all borrowers with DTIs greater than 36% or 43%, respectively. These fraction variables are proxies for K_{it}, which is the fraction of borrowers near payment constraints.

4.3 Mortgage interest rates

The mortgage interest rate, R, is the Freddie Mac 30-year fixed rate average for the United States, accessed via the Federal Reserve Bank of St. Louis' FRED dataset API using STATA. This series is weekly in its raw state, and is aggregated to quarterly based on the within-period average. Other interest rates are also considered, including the Federal Funds Rate and the 10-year Treasury rate.

4.4 Wage income

To capture a reliable, granular, high-frequency measure of income, Y, I use the Bureau of Labor Statistic's Quarterly Census of Employment and Wages (QCEW). This dataset includes a county-level census of average weekly earnings, which is aggregated to CBSA/CBSADs using employment shares from the same dataset. This particular income measure has the added benefit that it likely represents the marginal borrower, which has income primarily through wage earnings as opposed to capital or financial instruments.

4.5 Maximum loan amount

The maximum loan amount measure is calculated as $B_{it} = \bar{K}_t Y_{it}/R_t$. It is important to be clear from the outset that this measure is not to be taken literally: while average incomes and interest rates are averages and thus have clear interpretations for infinitely-lived interest-only loans, leverage, amortization, and other loan and borrower characteristics vary. Additionally, the credit standards measure is imperfect, as it reflects Enterprise loans, borrowers can affect their own DTIs by reporting more income, and DTIs can rise above strict Enterprise or FHA limits on the private market by paying higher interest rates. Accordingly, the measure of B is best interpreted as a maximum loan amount *index*, scaled to give plausible loan amounts that are easily interpretable.

4.6 Summary statistics and time series properties

The five main variables whose properties are considered include house prices, the maximum loan amount, and the three components of the maximum loan amount which include the national mortgage interest rate, the national credit standards measure, and the local average wage income. In addition, the three debt service-to-income (DTI) measures are summarized. Summary statistics for these variables are presented in Table 1. The mean quarterly growth rate for house prices is 1.2%, with wages increasing by 0.8%. The average mortgage interest rate over the sample was 5.3%. Importantly, over the sample, the maximum loan amount rose by 1.9% per quarter, largely due to increases in wages and the decline in interest rates. The disequilibrium measures, which give the percentage house price levels are overvalued relative to economic fundamentals, and calculations of which are to follow, show an average disequilibrium level of 0.2%, with a 90% interval of -22% to 28%. This suggests that at times, house prices departed substantially from economic fundamentals.

Correlations are calculated across variables within city-periods over cities and time. House prices have a small positive quarterly correlation with wages and a negative correlation with the mortgage rate. Each of the DTI measures is highly correlated within cities. Payment constraints are negatively correlated with house prices.

Across the 100 city sample, the median optimal lag length of the bivariate system $\mathbf{x} = [y\ b]'$ is 4 with some cities necessitating 2 or as many as 7, according to AIC values. Based on Dickey and Fuller (1979) regressions with a constant term but no trend using MacKinnon (1994) 10% critical values, house prices are I(1) in 98 of 100 cities, with two estimated to be I(2) (Los Angeles and Sacramento, CA).[12] Income and the maximum loan amount is I(1) in all 100 cities, and the two national measures are both I(1).

[12] As defined by Engle and Granger (1987), a series with no deterministic components which has a stationary, invertible, ARMA representation after differencing d times is said to be integrated of order d, denoted $I(d)$.

5 Cointegration Results

5.1 Long-run model

Estimates from the first-stage cointegrating regression models in equation 6 show substantial variation in parameters across cities. When the baseline model (BASE) is estimated without factor-augmented residuals, the smallest $\hat{\beta}_{i1}$ is 0.14 for Detriot, MI, and the largest is 0.78 for Los Angeles, CA. The mean group estimate (Pesaran and Smith, 1995) is 0.48 and the median estimate is 0.50. These estimates are interpreted as three house price elasticities, with respect to: incomes ($\hat{\beta}_{i1}$), loan payment constraints ($\hat{\beta}_{i1}$), and mortgage interest rates (-$\hat{\beta}_{i1}$).

As predicted in equation 5, the elasticity of housing supply is negatively related to the strength of the relation between maximum loan amounts and house prices. In cities with low supply elasticities, demand increases are capitalized into prices at high rates, implying little supply response. However, in cities with high supply elasticities, demand increases do not affect prices very much, implying substantial construction responses.

The $\hat{\beta}_i$ parameters are shown in Figure 4 panel (a) versus the 2018 Wharton Land Use Regulatory Index (Gyourko et al., 2021), a variable in the housing literature that commonly is used as a determinant of or proxy for the elasticity of housing supply. After transforming $\hat{\beta}_{i1}$ into an estimate of the long-run elasticity of housing supply σ using the formula $\hat{\sigma}_i = \frac{1}{\hat{\phi}_i} = \frac{1-\hat{\beta}_{i1}}{\mu\hat{\beta}_{i1}}$ and assuming $\mu = 0.75$ (Albouy et al., 2016), this series is plotted in panel (b). The range of the elasticity is approximately 8 in the most supply elastic cities, to around 1 in the most supply inelastic cities. These estimates are within the range of Harter-Dreiman (2004), Green et al. (2005), and Baum-Snow and Han (2019), but somewhat higher on average than Saiz (2010). It is remarkable that the estimate of the elasticity of housing supply produced here includes no quantity information, instead inferring the elasticity only based on the strength of the relation between borrowing power and house prices, following Harter-Dreiman (2004).

When estimated using models accounting for cross-sectional dependence, parameter estimates differ wildly. The CCE estimator of Holly et al. (2010) gives estimates that do not make sense given our knowledge of the house price elasticity with respect to incomes, with many estimates below zero and above one, and an average estimate of 1.15.[13] Additionally, the CCE estimate of β_{i1} has a 0.01 correlation with the BASE estimates across the 100 cities.[14] The CDP estimator of Teal and Eberhardt (2010) gives β_{i1} estimates that are much smaller, but fairly correlated with the BASE specification, with a correlation of 0.34 (and a correlation of 0.05 with the CCE estimator).[15] The mean group effect, however, is only 0.08. For full estimates see appendix table A.1. Most problematic is the CCE estimator, whose issues have been noted by Pedroni (2007). In this model, the estimated cointegration parameters are no longer super-consistent because the common trends are removed by including the period means, thus re-introducing problems caused by simultaneity and omitted variables. Accordingly, the BASE and CDP disequilibrium measures are preferred, with BASE measures put head-to-head in encompassing tests conducted on estimates from short-run dynamic models.

5.2 Short-run models

Next, cointegration tests are conducted over each of the individual cities using measures of disequilibrium from the OLS regressions. Johansen (1995) tests reject the null of one or more cointegrating vectors in 98 out of 100 cities, leaving two with evidence of cointegration (Providence, RI, and Tacoma, WA). Banerjee et al. (1998) tests reject the null of no cointegration in 15 cities. In sum, estimated independently, there is weak evidence for a cointegrating relation between house prices and maximum loan amounts.

Cointegration tests that are estimated across the panel reveal a different story. Westerlund (2007) tests, after accounting for cross-sectional dependence, reject the null of no cointegration for *all* units in the panel at the 10% level using two distinct group means tests, and for *any* units in the panel at a 0.1% level using two distinct panel tests. Based on these panel cointegration tests, cointegration seems likely in most cities.

Finally, I turn to falsification tests of the restriction that the parameters on k_t, y_{it}, and r_t are each equal to β_{i1}. This is a key prediction of the theory in Section 2, and fundamental to the empirical strategy of anchoring mortgage interest rates to incomes and borrowing

[13] The CCE controls that define F are the means across cities within time periods, or $\bar{p}_t$ and $\bar{b}_t$.

[14] The problematic nature of the estimates produced by the CCE estimator is also noted by Oikarinen et al. (2018).

[15] The CDP controls that define F are calculated using an auxiliary regression of first-differences of p and b on differenced time dummies. The estimated time dummy parameters are then used as controls in the cointegrating regression.

constraints in the cointegration analysis. My approach involves a series of encompassing tests of alternative cointegrating regressions, inserted separately and then together, into equation 8. Eight alternative right-hand-sides of the cointegrating equation are considered in addition to the primary one specified in equation 6. These are used to calculate alternative disequilibrium measures for use in second-stage dynamic models. The first six are estimated using OLS: income alone; incomes and interest rates (unrestricted); incomes, interest rates, and borrowing constraints (unrestricted); incomes and interest rates (restricted equal and opposite signs); b, but using a 30 year amortization period for discounting; and b, but using the 10-year Treasury rate. The final two consider b, but with CCE and CDP controls.

The results of dynamic models with these alternative measures are summarized in Table 2, offering several findings. First, as the first nine models show, each disequilibrium measure has similar estimates of mean reversion, at 3-4% per quarter, with the exception of the CCE model which has no mean reversion. After the CCE model, models with interest rates entering unrestricted have the highest in-sample root mean-squared errors (RMSE), suggesting inclusion along with income harms predictive power. Models with a single term, be it income, income and interest rates (restricted) or income, interest rates, and borrowing constraints (restricted), each are tied for the lowest RMSE, along with the alternative amortization term (30 year) and interest rate (10-year Treasury).

When each disequilibrium measure is put head-to-head with the BASE model, the baseline maximum loan amount equilibrium correction term is the only one that is both negative and significant, with all other measures either turning insignificant or positive. Together, this suggests that the maximum loan amount measure outperforms alternatives where it matters most: in explaining appreciation rates of housing and providing the most unique and relevant information.

5.3 Summary

This section establishes a cointegrating relation exists between house prices, interest rates, incomes, and borrowing constraints. These variables enter with restrictions placed on the cointegrating parameters, with incomes and borrowing constraints having equal signs, and interest rates having an equal but opposite sign. The economic interpretation of these restrictions is as a maximum loan amount measure. Estimators that augment residuals with factors, such Holly et al. (2010) and Teal and Eberhardt (2010), perform worse than those estimated using OLS in second-stage dynamic models. Accordingly, the preferred disequilibrium measure uses the cointegration equation with restricted incomes, interest rates, and borrowing constraints, estimated without residual augmentation (the BASE model). The sections that follow use this particular disequilibrium measure to examine the channels by which mortgage rates affect house prices.

6 Effects of Interest Rates and Payment Constraints

This section estimates the effect of a single, permanent change in mortgage interest rates on house prices. The operating hypothesis in this section is that there are differences in $\boldsymbol{\alpha}_i$ across cities, that is, the parameters that determine a city's speed of adjustment to its long-run equilibrium. The interest rate has a mechanical relation to debt service payments for new borrowers, holding loan amounts and all other variables constant. Accordingly, interest rate changes affect the fraction of payment-constrained borrowers in a city K_{it}, potentially making such cities more responsive to interest rate changes with faster rates of adjustment (Greenwald, 2018).

Building on equation 8 and focusing on the house price equation, a dynamic model of house prices with factor-augmented errors is

$$\Delta p_{it} = a_i + \alpha_0 \hat{u}_{it-1} + \alpha_1 \hat{u}_{it-1} \times K_{it-1} + \sum_{j=1}^{J} d_{1j} \Delta p_{it-j} + \sum_{j=1}^{J} d_{2j} \Delta b_{it-j} + e_{it} \tag{9}$$

where $e_{it} = \boldsymbol{\lambda}_i' \boldsymbol{F}_t + \epsilon_{it}$. From this base equation, specifications diverge concerning $\boldsymbol{\lambda}_i' \boldsymbol{F}_t$, as was the case of the long-run model. This general representation of a factor structure encompasses time period fixed effects, common correlated effects (CCE) estimators in the vein of Holly et al. (2010), or factors estimated using principal components analysis as do Greenaway-McGrevy et al. (2012). One empirical challenge is choosing the structure of $\boldsymbol{\lambda}_i' \boldsymbol{F}_t$ so that cross-sectional dependencies are absent from e_{it}. Saturation of this term with a multitude of variables or factors is sure to achieve this goal, but at the cost of absorbing potentially useful explanatory power with no available interpretation. It is thus best to be parsimonious as possible, both to achieve an efficient estimator and to achieve useful identification of the desired effect, in this case, interest rates. Two augmentations are considered, time period fixed effects and CCE terms, the latter of which enters as means of both right-hand side and left-hand side variables ($\Delta \bar{p}_t$, $\Delta \bar{p}_{t-1}$, $\Delta \bar{p}_{t-2}$, $\Delta \bar{p}_{t-3}$, $\bar{u}_{t-1}$, $\overline{u_{t-1}}K_t$,

$\Delta\bar{b}_{t-1}$, and $\Delta\bar{b}_{t-2}$) with loadings that are city-specific following Holly et al. (2010). The time period fixed effects use 102 degrees of freedom whereas the CCE controls use 800 (100 cities $\times$ 8 variables), not counting those with multicollinearity with respect to other variables or sets of variables. This is 1% and 8% of the sample, respectively.

There are three possible channels that are considered. The first channel is the change in the long-run fundamental value of housing. The second is the speed of adjustment of house prices to its long-run fundamental value. The final channel is the short-run effect of fluctuations in the maximum loan amount, which is mechanically related to the prevailing mortgage interest rate.

The partial derivative of equation 9 with respect to r_{t-1} (ignoring the factor-augmented residuals) is

$$E\left[\frac{\partial \Delta p_{it}}{\partial r_{t-1}}\right] = \underbrace{\frac{\partial \Delta p_{it}}{\partial \hat{u}_{t-1}}\frac{\partial \hat{u}_{it}}{\partial r_{t-1}}}_{fundamentals\ effect} + \underbrace{\frac{\partial \Delta p_{it}}{\partial K_{t-1}}\frac{\partial K_{it-1}}{\partial r_{t-1}}}_{adjustment\ speed\ effect} + \underbrace{\frac{\partial \Delta p_{it}}{\partial \Delta b_{t-1}}\frac{\partial \Delta b_{it-1}}{\partial r_{t-1}}}_{short-run\ effect} \tag{10}$$

In this expression, the interest rate can have three effects, with operational hypotheses to follow. The first is through deviations from the long-run fundamental value, u_{it}. An interest rate change, all else equal, causes the disequilibrium term to fall, i.e. if interest rates rise, the fundamental house price falls, creating a positive disequilibrium or $\partial \hat{u}_{it}/\partial r_{t-1} > 0$. Then, as is standard in an equilibrium correction model, $\partial \Delta p_{it}/\partial \hat{u}_{t-1} < 0$. Multiplied,

$$\frac{\partial \Delta p_{it}}{\partial \hat{u}_{t-1}}\frac{\partial \hat{u}_{it}}{\partial r_{t-1}} < 0$$

In models with time period fixed effects, this equation is identified by variation in β_{i1} interacted with changes in r_{it-1}, that is, the long run elasticity of house prices with respect to maximum loan amounts. Level effects are not identified in models with time period fixed effects.

The second effect is through the speed of adjustment to equilibrium. The fraction of borrowers near payment constraints K_{it} is positively related to the interest rate, so interest rate is positively related to this share such that $\partial K_{it}/\partial r_{it} > 0$. Then, the effect of borrowing constraints on house prices is through the disequilibrium term. However, a high fraction of borrowers near payment constraints may only increase the speed of adjustment when the disequilibrium is positive, that is, when house prices are overvalued based on fundamentals. There is no reason to believe that an already-high fraction of constrained borrowers will help to increase house prices in periods of negative disequilibrium. Therefore, an asymmetric effect is hypothesized, and $\partial \Delta p_{it}/\partial K_{it} < 0$ only if $\hat{u} > 0$.

$$\frac{\partial \Delta p_{it}}{\partial K_{t-1}} \frac{\partial K_{it-1}}{\partial r_{t-1}} \begin{cases} = & 0, \quad \text{if } \hat{u}_{it-1} \leq 0 \\ < & 0, \quad \text{if } \hat{u}_{it-1} > 0 \end{cases}$$

The final is the short-run dynamic response through Δb. This effect is hypothesized to be negative by first-differencing the long-run equation 6 and noting that r_{t-2} is fixed.

$$\frac{\partial \Delta p_{it}}{\partial \Delta b_{t-1}} \frac{\partial \Delta b_{it}}{\partial r_{t-1}} < 0$$

This effect is not identified in any model with time period fixed effects or CCE controls because variation in r is constant across locations within periods, and thus absorbed by other covariates.

6.1 Results

Table 3 presents estimates of variations of the model represented by equation 9. The preferred DTI variable is $DTI43$, which is the share of borrowers in a city with a back-end DTI greater than or equal to 43% of monthly income, and the preferred augmentation to residuals is time-period fixed effects. Following these choices gives estimates of the best fit while giving cross-sectional correlations of residuals that approach zero.

The first column presents a model with no time-period fixed effects. The next three columns consider alternative measures of payment constraints while including time-period fixed effects. The next controls for cross-sectional dependence with a set of mean group effects following Holly et al. (2010). The final two columns model the hypothesized asymmetric response to positive versus negative disequilibrium states using both time-period fixed effects and CCE controls.

6.1.1 Long-run fundamentals effect

By altering the long-run fundamental value of housing, interest rates put house price changes on a path to that equilibrium. The change to that equilibrium need not to occur all at once or even quickly. Instead, evidence suggests effects are small on a per-period basis, but accumulate at longer time horizons.

The parameters on $\hat{u}$ and $\hat{u} \times K_{it}$, using various measure of DTI as proxies for K, indicate reversion of house prices to the estimated long-run fundamental value. When $\hat{u}$ enters alone, its parameter is not statistically significant from zero. However, when $\hat{u}$ is interacted with various DTI measures, this parameter is significant and negative across all specifications. While each measure of DTI gives similar in-sample RMSEs, but the share of borrowers within a city with $DTI \geq 43$, is the preferred expression because this most closely resembles a value representing a borrowing constraint, especially in recent periods where Dodd-Frank qualifying mortgage (QM) rules are in effect. This estimated model is shown in column 4 of table 3. Using this model's estimates the effect of interest rates on house prices via the change to long-run fundamental values, evaluated at the mean $\hat{\beta}_{i1}$ of 0.48, and using α_0=0 and $\hat{\alpha}_1 = -0.12$ in model 4,

$$E[\frac{\partial \Delta p_{it}}{\partial \hat{u}_{t-1}} \frac{\partial \hat{u}_{it}}{\partial r_{t-1}}] = -\hat{\beta}_{i1}(\hat{\alpha}_0 + \hat{\alpha}_1 DTI43_{it}) = -0.057 DTI43_{it}$$

Evaluated the mean DTI43 of 0.23, this partial effect suggests that a 0.1 log-change in the mortgage interest rate gives a -0.12% change to house prices in the first period following the change (for context, going from 4% to 5% mortgage rates is a 0.22 log-change). This effect will accumulate in a dynamic context as disequilibrium diminishes over time and lags of price changes influence future appreciation rates.

6.1.2 Adjustment speed effect

Interest rates mechanically affect the maximum loan amount a borrower can afford. As demonstrated in Section 2, the higher the interest rate, the lower the maximum loan amount. A corollary to this concept is that for the same loan amount, an interest rate increase will increase the monthly payment. We would therefore expect interest rates and the share of debt service-constrained borrowers to be positively linked. This point is made thoroughly by Greenwald (2018), who shows in a DSGE model of the U.S. economy how interest rate increases serve to make payment constraints binding for a larger fraction of borrowers, and how this can affect propagation of interest rate shocks.

Figure 1 shows the median share of borrowers across cities with DTIs greater than 43, plotted alongside the 30 year fixed-rate mortgage series. Visual inspection strongly suggests a positive relation between interest rates and high DTIs. Modeling the log difference of DTI43 (lowercase) as a function of a constant term and the lagged log of the interest rate gives the effect of the mortgage interest rate on the share of borrowers in a city facing payment constraints.

$$\Delta dti43_{it} = a + \zeta \Delta r_{t-1} + w_{it} \tag{11}$$

This extremely parsimonious model projects DTI43 onto mortgage rates quite well relative to other models.[16] The estimate of ζ is 0.29 with a standard error of 0.12, suggesting a 0.1 log-change in the mortgage interest rate gives a 0.03% change in the share of Enterprise borrowers with a DTI greater than or equal to 43. In levels, a change in mortgage interest rates from 4% to 5% gives a 6% increase in DTI43; at the mean DTI43 of 23%, this would be an 1.4 percentage point increase to 23.4%. In terms of partial derivatives with respect to prices, using $\hat{\zeta} = 0.29$ and $\hat{\alpha}_1 = -0.12$,

$$E[\frac{\partial \Delta p_{it}}{\partial K_{t-1}} \frac{\partial K_{it}}{\partial r_{t-1}}] = \hat{\alpha}_1 \hat{\zeta} \hat{u}_{it-1} = -0.03 \hat{u}_{it-1}$$

Evaluated at a 1 standard deviation disequilibrium measure of 0.15, this suggests a 0.1 log-change in mortgage interest rates gives a -0.05% change to house prices in the first period following the change in interest rates by quickening the speed of adjustment to the long-run equilibrium. Note that this is about 40% of the estimated 1-period effect due to altering the long fundamental house price.

When using model 6, which takes into account asymmetric effects, greater richness emerges.

[16] City fixed effects do not reject the null hypothesis that each is equal to 0; additional lags of $\Delta dti43$ and Δr cannot reject the null hypothesis that each is 0 at the 5% level.

If $\hat{u} \leq 0$, the parameters on $\hat{u} \times DTI43$ and $\hat{u}^{-} \times DTI43$ sum to zero, giving an adjustment speed effect of interest rates equal to zero as predicted. When taking into account the non-interaction terms by summing both non-interacted α parameters, the total per-period equilibrium correction is about -0.05 of the disequilibrium per quarter. When $\hat{u} > 0$, the α_1 parameter is -0.36 vs -0.12 in model 3. Accordingly, the partial effect is substantially higher, at -0.10 vs -0.034. However, when the total equilibrium correction effect for model 6 is evaluated, because $\alpha_0 = 0.10$, equilibrium correction is nearly zero at the mean DTI43. Only when the share of DTI43 moves beyond 27% does equilibrium correction occur. Model 6 thus provides some evidence of important threshold effects: when at negative disequilibrium, equilibrium correction is slow, steady, and unrelated to payment constraints; when at positive disequilibrium, adjustment is nonexistent unless payment constraints are binding for a large fraction of borrowers, after which adjustment accelerates.

6.1.3 Short-run effect

Short-run effects are potentially large but uncertain, with quarterly fluctuations in interest rates serving as noisy predictors of future house price appreciation. The first thing to note is that this effect is only identified in model 1, because the partial effect is subsumed within controls in the other models. Model one has a large residual correlation across cities, however, so this model may suffer from omitted variable bias. Nontheless, lacking a better identification strategy, these effects are used. The expected partial effect is as follows, where $\hat{d}_1 = 0.03$ and the mean $\hat{\beta}_{i1} = 0.48$,

$$E[\frac{\partial \Delta p_{it}}{\partial \Delta b_{t-1}} \frac{\partial \Delta b_{it-1}}{\partial r_{t-1}}] = -\hat{\beta}_{i1}(\hat{d}_1) = -0.015$$

This equation suggests a 0.1 log-change in mortgage interest rates gives a -0.15% change to house prices in the first period following the change in interest rates.

6.1.4 Combined effects

Together, these estimates suggest that a 0.1 log-change in mortgage interest rates results in the following changes to house prices in the following quarter: a long-run effect of -0.12%, an adjustment speed effect that depends on the initial state of disequilibrium, and a short-run effect of -0.15%. Combined, this gives a 1-quarter interest rate-house price appreciation elasticity of between -0.01 and -0.05 depending on the initial disequilibrium state. This is an order of magnitude smaller than the long-run elasticities from the cointegrating regressions which ranged from -0.2 to -0.8. Evaluated at a 1-quarter elasticity of -0.03 and a long-run elasticity of -0.5, a permanent change in mortgage interest rates from 4% to 5% gives a partial house price change of -0.7% after one quarter and -10.7% in the long-run, relative to baseline rates.

How do these estimates compare to the existing literature? McQuinn and O'Reilly (2008) estimate a quarterly equilibrium correction effect of about -0.05 with no other interest rate dynamics, suggesting a quarterly elasticity of -0.05 given their version of $\hat{\beta}_1 = 1.0$, estimated over the country of Ireland. The results in this paper are thus similar, though the channels by which interest rates affect dynamics are somewhat different. Oikarinen et al. (2018) estimates panel equilibrium correction models across U.S. cities finding a mortgage interest rate effect of 0, though with an equilibrium correction term of -0.05, nearly identical to McQuinn and O'Reilly (2008). Gorea et al. (2022) estimates shocks to Federal Funds rates making their results difficult to compare to the estimates in this paper, though hopefully their work will allow direct comparisons in the future.

6.2 Horizon Effects

The models in this paper suggest interest rates enter into models of house prices largely by altering the long-run fundamental price and the speed of adjustment to that price. The question in this section turns to the effects of interest rate changes on house prices at various time horizons.

Define an h-step ahead change in price from a base period as $\Delta p_{i,t+h,t} = p_{it+h} - p_{it}$. This is modeled conditional on information known at time t, with h-specific parameters.

$$\Delta p_{i,t+h,t} = a_{hi} + a_{ht} + \alpha_{h0}\hat{u}_{it} + \alpha_{h1}\hat{u}_{it} \times DTI43_{it} + \sum_{j=1}^{J} d_{h1j}\Delta p_{it-j+1} + \sum_{j=1}^{J} d_{h2j}\Delta b_{it-j} + e_{i,t+h,t} \tag{12}$$

This equation is estimated using separate regressions for each time horizon. Figure 5 traces out $\hat{\alpha}_{h0} + \hat{\alpha}_{h1} \times DTI43_{it}$ along with 90% confidence intervals for $\hat{u}_{t-1} = 0$, the mean $DTI43_{t-1} = 0.23$, and the mean $\hat{\beta}_{i1}$ from the long-run regression of 0.48. The flat dotted line is the long-run effect, which when multiplying the mean of $\hat{\beta}_{i1}$ by $\ln 3.25 - \ln 3 = 0.08$ gives about -4% versus baseline appreciation after four years. We can see that the h-step models approach the long-run estimate around this time.[17]

The estimated change in house prices due to a level shift in interest rates is different for different base levels due to the natural log functional form, which is motivated by the presence of the interest rate in the denominator of the infinite sum of payments from equation 2. Accordingly, a rate change from 3% to 3.25% has about twice of the effect of a change in rates from 6% to 6.25%, as shown in figure 6 to be about -4% vs -2% after four years.

Effects of the share of payment constrained borrowers on interest rates are considered alongside house price elasticity differences because the two are so highly correlated and they both have important effects that interact. Regressing the cross-sectional means of DTI43 on the Wharton Residential Land Use Regulatory Index (WRLURI) gives the estimated equation, $\hat{D}TI43_i = 22.1(0.33) + 3.98(0.56) \times WRLURI_i$, with an R^2 of 0.36 (scatterplot with linear fit in the Appendix). Accordingly, to estimate the effect of a change in interest rates on house prices for areas with high and low elasticities of housing supply, an auxiliary equation is estimated to choose the evaluated interest rate elasticity. This auxiliary equation maps long-run elasticities to WRLURI values, with standard errors in parentheses. The equation estimated is $\hat{\beta}_{i1} = 0.455(0.013) + 0.124(0.022)WRLURI_i$, giving $\beta_{i1}^{lowreg} = 0.37$ at the 5th percentile value of the WRLURI of -0.7 and $\beta_{i1}^{highreg} = 0.62$ at the 95th percentile value of the WRLURI of 1.3. Long-run elasticities are also highly associated with payment-constrained borrowers, so the scenario considered here is to compare a hypothetical area at the 5th percentile of $DTI43$ and the WRLURI with the 95th percentiles in each. After four years, the effect of a change in interest rates from 3% to 3.25% on house prices is -2.3% in the 5th percentile city and -5.3% in the 95th percentile city. These results imply that supply-elastic areas may be more insulated from interest rate changes than supply-inelastic areas in the long-run.

Finally, asymmetric effects are considered. Figure 8 shows three sets of estimated partial effects of a change in rates from 3% to 3.25%: with an initial negative disequilibrium of 15% evaluated at the median $DTI43$, and with an initial positive disequilibrium of 15%, evaluated at the median and 95th percentile $DTI43$. Recall the model in Table 3 suggests threshold

[17]Note that these are partial estimates, not impulse-response functions. While the h-step ahead models provide direct estimates of interest rate changes, these are not interest rate *shocks* nor are usable to measure feedback between house prices and maximum loan amounts. Successive interest rate changes are additive such that offsetting interest rate movements in a short amount of time will have little partial effect on prices.

effects; in areas with positive disequilibrium, convergence occurs only when DTIs are high. Using h-step models, we see that this threshold effect is weaker than in the 1-step case from Table 3. Indeed, positive convergence status gives steady house price changes, reducing house prices by about -3.8% vs baseline after four years. However, threshold effects in the case of positive disequilibrium is no longer apparent. While house prices converge much faster at first with higher $DTI43$, they both reach the same -6% partial effect vs baseline after four years. This exercise suggests areas with initially high DTIs will face greater responsiveness to interest rate changes, but by year 3, areas with low DTIs catch up.

7 Conclusion

This research extends the long tradition of estimating house price dynamics in panel regression frameworks in two main ways. First, building on the seminal papers of Malpezzi (1999), McQuinn and O'Reilly (2008), Holly et al. (2010), Gallin (2006, 2008), and Oikarinen et al. (2018), house prices are modeled in an equilibrium correction framework where dynamics are based on both short-run determinants and long-run economic fundamentals. Previously, it has been difficult to link interest rates to house prices due to the rapid fluctuations in the mortgage interest rate combined with the long cycles that define house price dynamics. The solution to this problem is to restrict interest rates to enter into the long-run fundamental house price along with borrowing constraints in a manner consistent with the ability-to-pay framework of McQuinn and O'Reilly (2008). This hypothesized long-run fundamental value is shown to dominate alternative (unrestricted) models in subsequent dynamic model performance in terms of predictive ability, thus lending credence to the notion that borrowing constraints and interest rates fundamentally drive house prices.

The second contribution is to link mortgage interest rates to the speed of adjustment in equilibrium correction models of house prices. By raising borrowing costs, mortgage rates increase the fraction of new and prospective borrowers in an area who are constrained by their monthly debt service-to-income ratios. This effect speeds the adjustment of high house prices back to their long-run fundamentals because it is more difficult for households to borrow ever-increasing amounts to facilitate continued appreciation.

Future research in this vein could seek to estimate effects of interest rates more directly, such as Gorea et al. (2022), who avoids the parameter saturation required in empirical panel specifications. The need to account for residuals that are correlated across cross-sectional units makes it fundamentally difficult to estimate the total effect of interest rate changes in panel frameworks.

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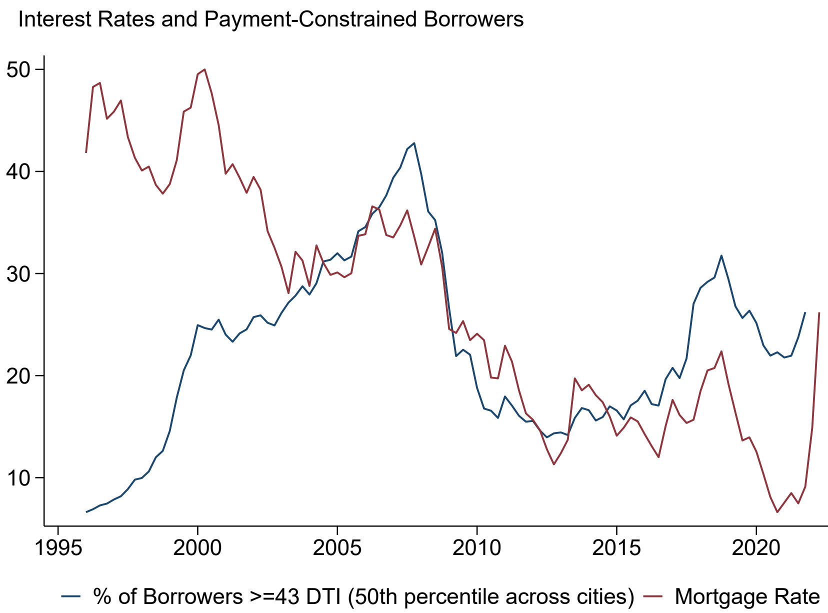
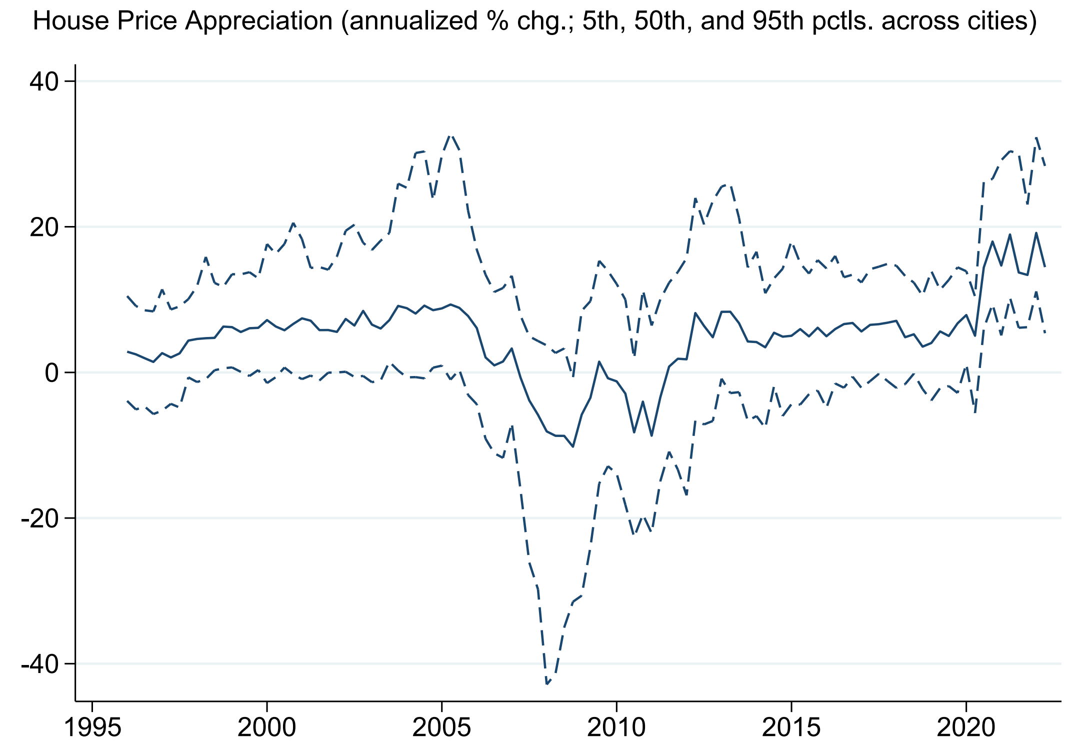
Figure 1: Mortgage Rates and Payment Constraints



Sources: The mortgage rate is Freddie Mac's, 30-Year Fixed Rate Mortgage Average in the United States [MORTGAGE30US], retrieved from FRED, Federal Reserve Bank of St. Louis, accessed 9/27/2022. Debt service-to-income ratio (DTI) is from internal FHFA data on Fanne Mae and Freddie Mac home mortgages, and calculated as the share of purchase-money mortgage borrowers with a back-end $DTI \geq 43$. The series shown is the 50th percentile share across cities, calculated in each quarter.

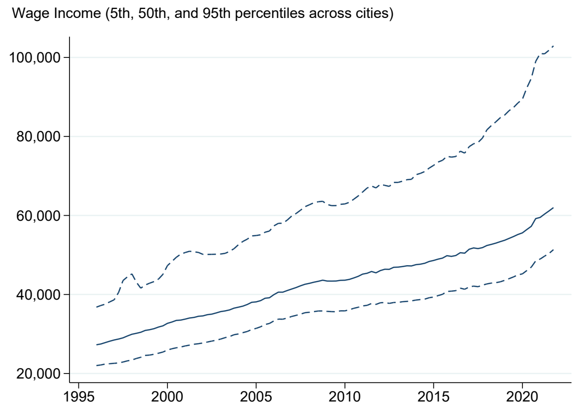
Figure 2: House Price Appreciation



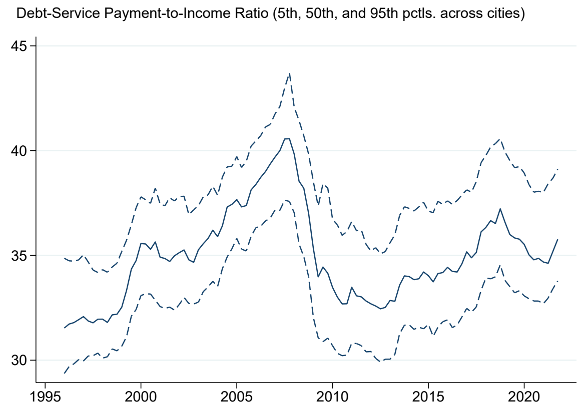
Source: Federal Housing Finance Agency "Expanded data" indices for 100 largest Metropolitan Statistical Areas (seasonally adjusted), accessed 9/27/2022. Annualized quarterly rates.

Figure 3: Time Series Statistics

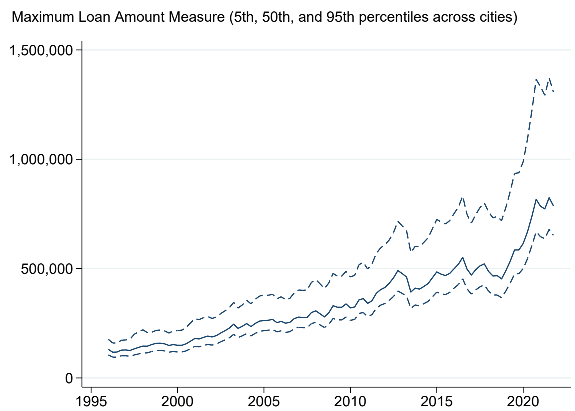
(a) Wage Income



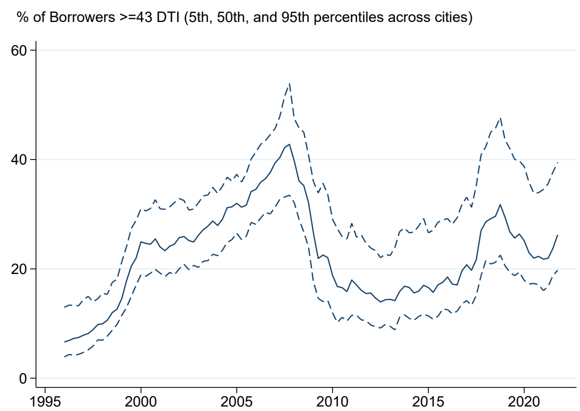
(b) Debt-Service Payment-to-Income Ratio



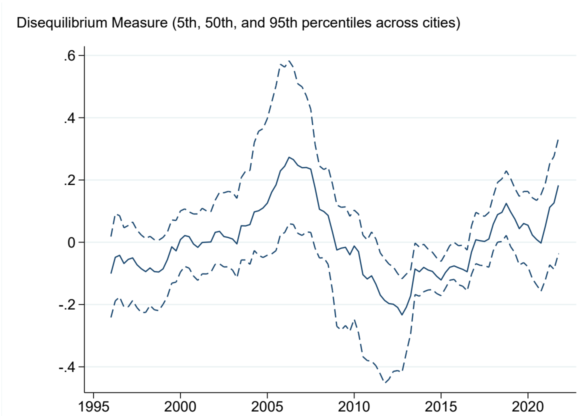
(c) Maximum Loan Amount



(d) Share of Borrowers with DTI$\geq$43



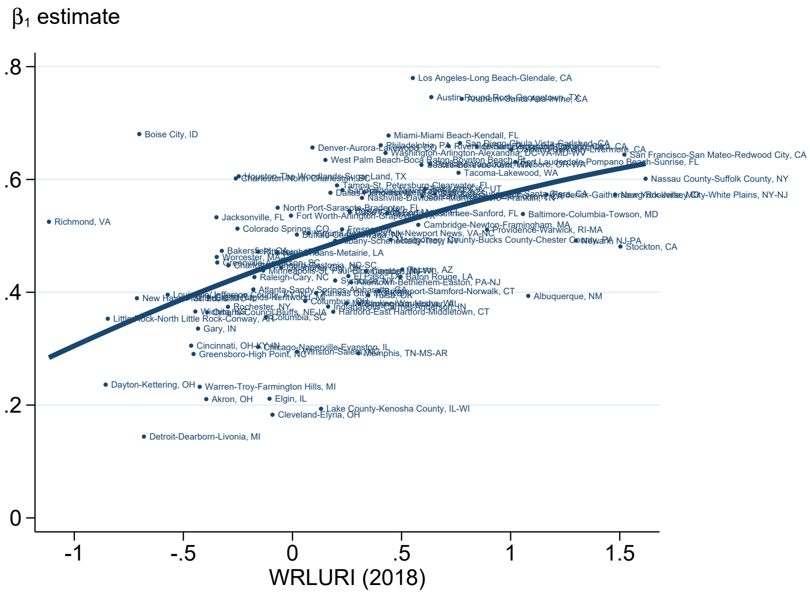
(e) Disequilibrium Measure



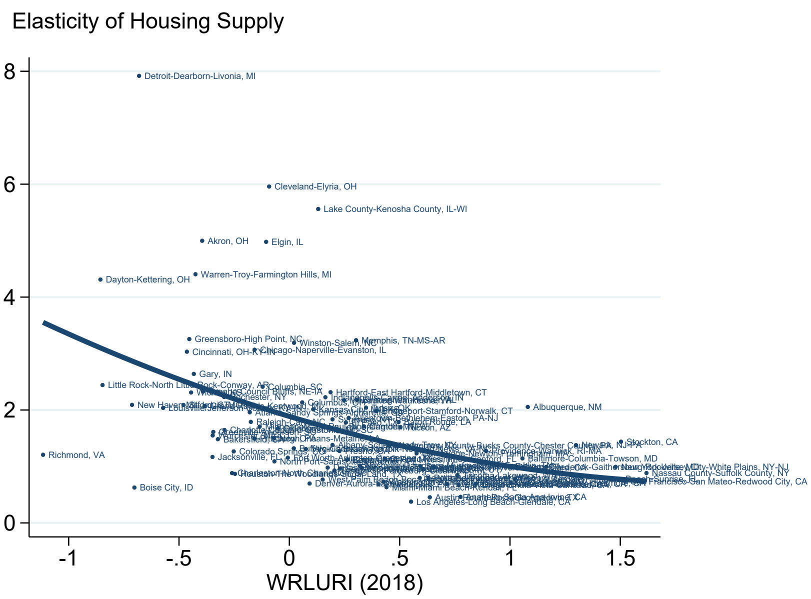
Sources: (a) Quarterly Census of Employment and Wages, produced by the Bureau of Labor Statistics; (b) Internal FHFA data; (c) Various sources described in main text; (d) Internal FHFA data; (e) Various sources described in main text.

Figure 4: Estimates from City-Specific Cointegrating Regressions

(a) Estimates of β_1

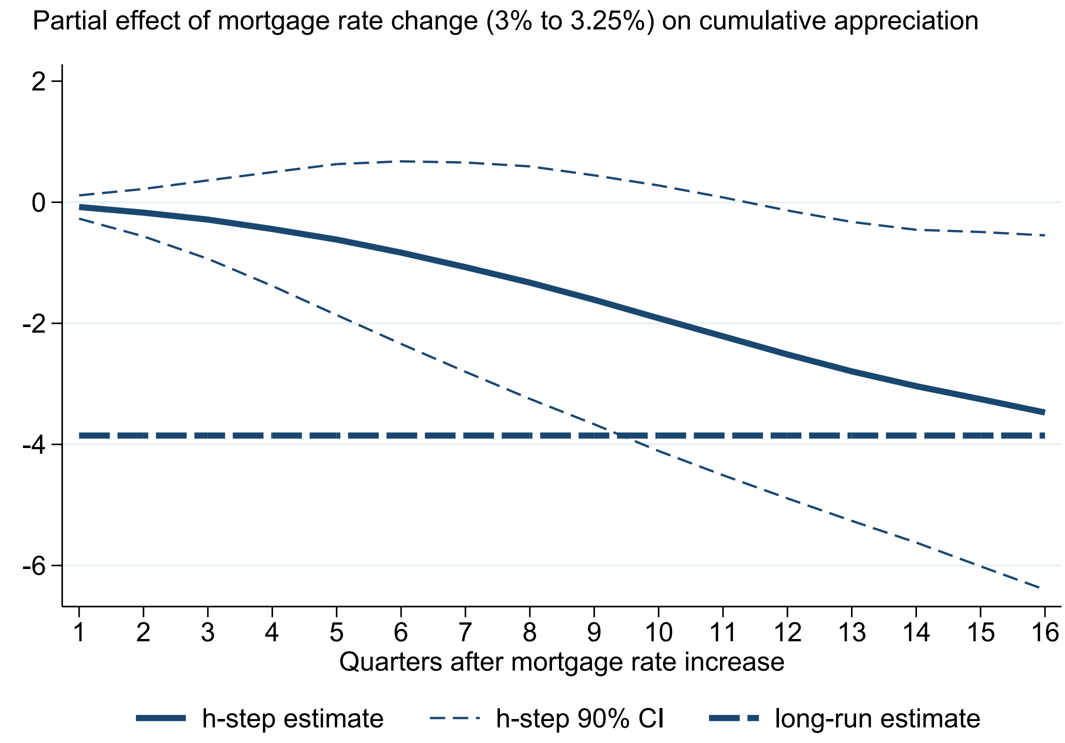


(b) Implied Estimate of Elasticity of Housing Supply



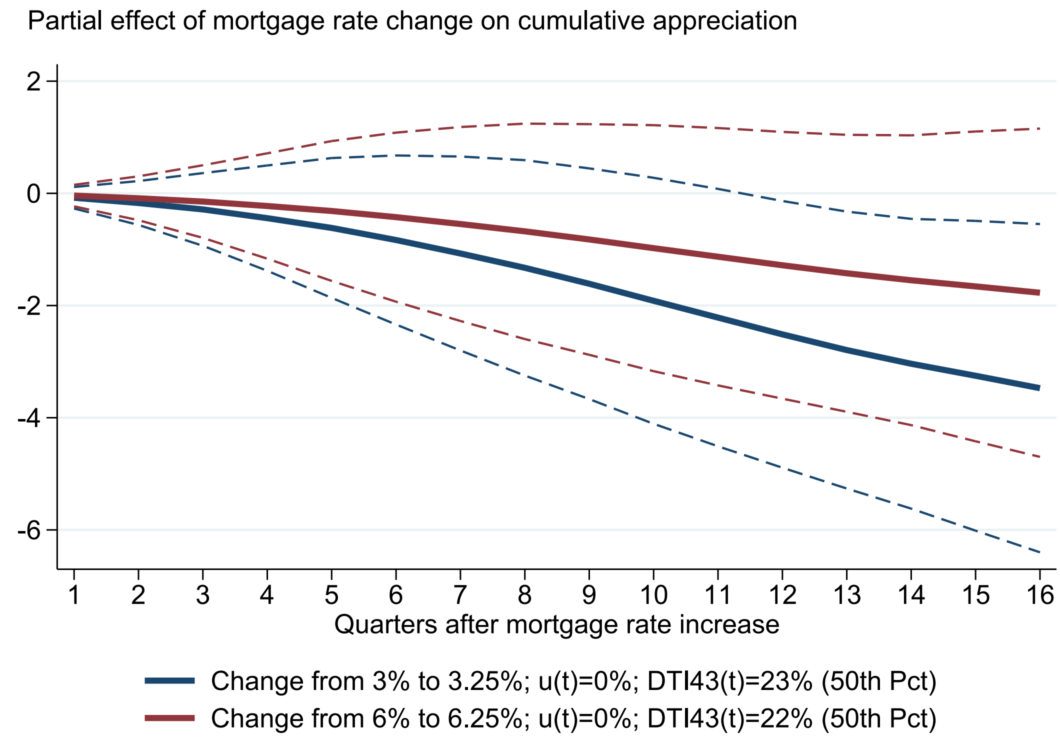
Sources: The Wharton Land Use Regulatory Index (WRLURI) is described by Gyourko et al. (2021).
Notes: Estimates in panel (a) are from long-run cointegrating regressions described in equation 6, and are interpreted as the house price elasticity with respect to incomes, payment constraints and the negative of the interest rate. Panel (b) presents a transformation of estimates in panel (a), $\sigma_i = \frac{1}{\hat{\phi}_i} = \frac{1-\hat{\beta}_{i1}}{\mu\hat{\beta}_{i1}}$, assuming $\mu = 0.75$ following Albouy et al. (2016).

Figure 5: Partial Effects of Mortgage Rate Changes on House Prices



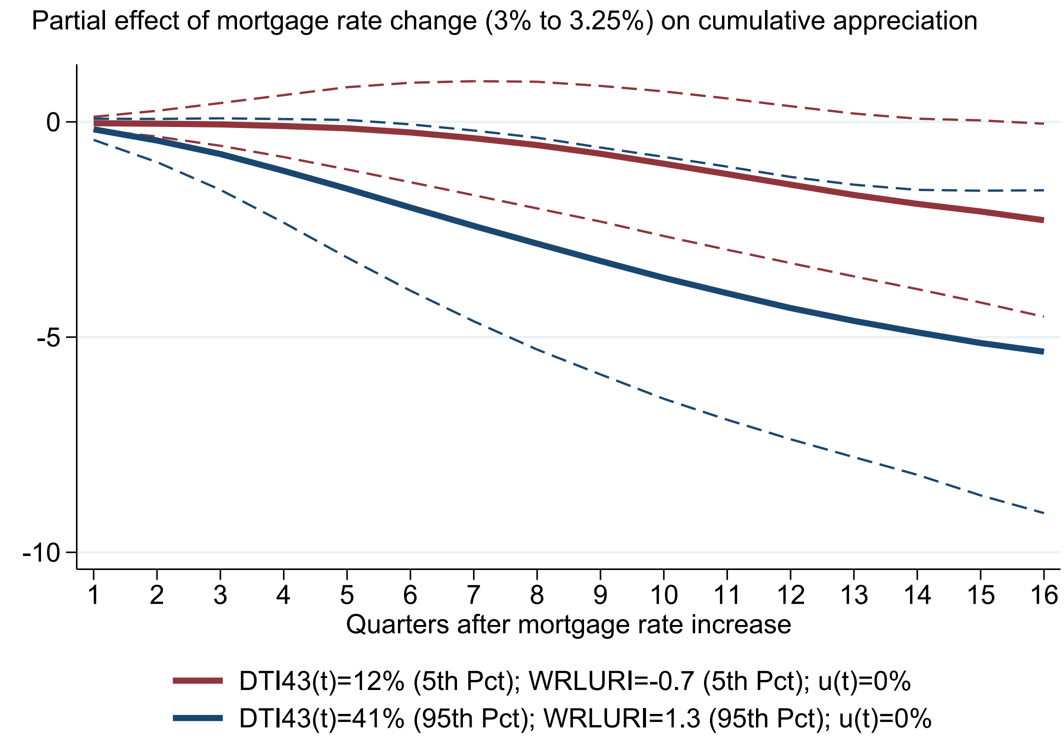
Notes: h-step estimates are based on the equation:
$\partial \Delta p_{t+h,t}/\partial r_t = \hat{\beta}_1^p(\hat{\alpha}_0 \hat{u}_t + \hat{\alpha}_1 \hat{u}_t DTI43_t^p)(r_t - r_{t-1}) * 100$. The superscript p indicates the percentile (in this case, the 50th for both $\hat{\beta}_1$ and $DTI43$), and all α parameters are estimated in a new regression for each horizon. Dotted lines indicate a 90% confidence interval, calculated analytically. The long-run estimate is from the long-run cointegrating equation, and is calculated as the negative of the Pesaran and Smith (1995) mean group estimate, or $-100^{-1} \sum_i^{100} \hat{\beta}_{i1}$.

Figure 6: Partial Effects of Mortgage Rate Changes on House Prices by Initial Rate



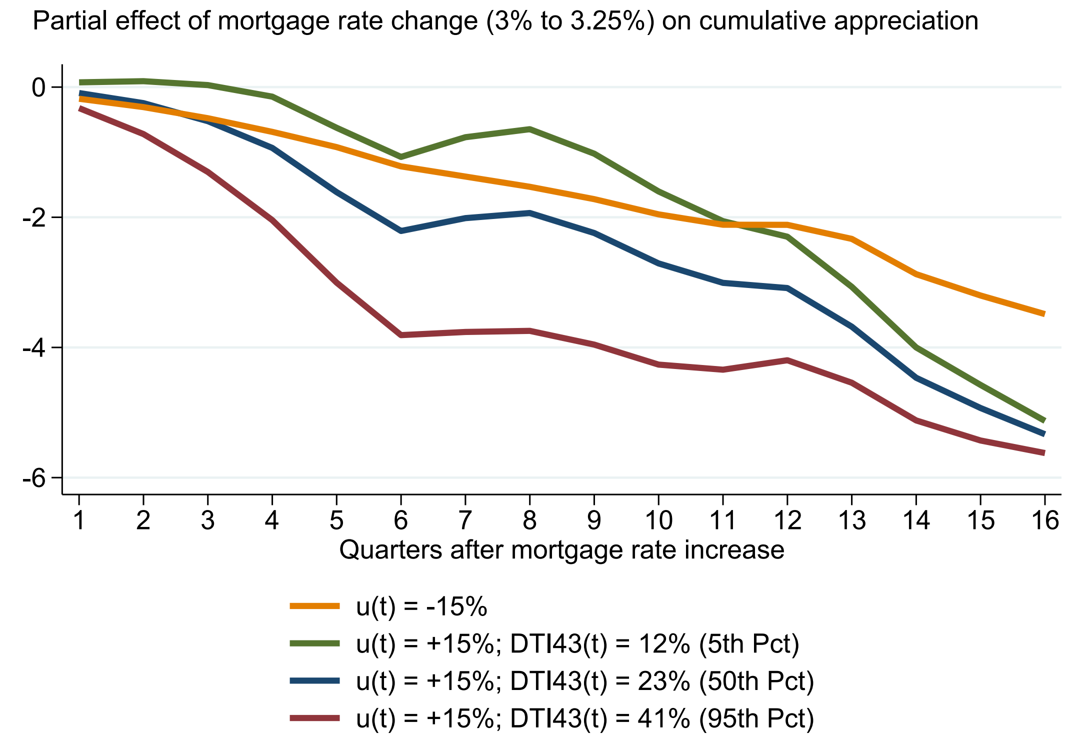
Notes: Estimates are based on the equation: $\partial \Delta p_{t+h,t}/\partial r_t = \hat{\beta}_1^p(\hat{\alpha}_0 \hat{u}_t + \hat{\alpha}_1 \hat{u}_t DTI43_t^p)(r_t - r_{t-1}) * 100$. The superscript p indicates the percentile, and all α parameters are estimated in a new regression for each horizon. Dotted lines indicate a 90% confidence interval, calculated analytically.

Figure 7: Partial Effects of Mortgage Rates on House Prices by DTI and Land Use Regulation



Notes: Estimates are based on the equation:
$\partial\Delta p_{t+h,t}/\partial r_t = (\hat{\gamma}_0 + WRLURI^p\hat{\gamma}_1)(\hat{\alpha}_0\hat{u}_t + \hat{\alpha}_1\hat{u}_t DTI43_t^p)(r_t - r_{t-1}) * 100$. The γ parameters are estimated based on an auxiliary regression of estimated long-run elasticites as a function of the Wharton Residential Land Use Regulatory Index (WRLURI) (Gyourko et al., 2021), $\hat{\beta}_{i1} = \gamma_0 + \gamma_1 WRLURI_i + v_i$. The superscript p indicates the percentile, and all α parameters are estimated in a new regression for each horizon. Dotted lines indicate a 90% confidence interval, calculated analytically.

Figure 8: Partial Effects of Mortgage Rates on House Prices by Initial Disequilibrium



Notes: Estimates are based on the equation:
$\partial \Delta p_{t+h,t}/\partial r_t = \left(\hat{\beta}_1^p(\hat{\alpha}_0 \hat{u}_t + \hat{\alpha}_0^- \hat{u}_t^- + \hat{\alpha}_1 \hat{u}_t DTI43_t^p + \hat{\alpha}_1^- \hat{u}_t^- DTI43_t^p) + \hat{\zeta}(\hat{\alpha}_1 \hat{u}_t + \hat{\alpha}_1^- \hat{u}_t^-)\right)(r_t - r_{t-1}) * 100.$
In this equation, u^- has a value of 0 if u is positive or u otherwise, the superscript p indicates the percentile, and all α and ζ parameters are estimated in a new regression for each horizon.

Table 1: Summary Statistics

Variable	Name	Type	Units	Mean	SD	5th Pct.	50th Pct.	95th Pct.	Source
P	House price appreciation	Panel	log-difference*100	1.2	2.4	-2.7	1.3	4.8	Federal Housing Finance Agency
W	Wages	Panel	log-difference*100	0.8	1.4	-0.4	0.8	2.1	Bureau of Labor Statistics
R	Mortgage interest rate	Series	level %	5.3	1.5	3.1	5.0	7.8	Freddie Mac
K	*Debt service-to-income (DTI)*	Panel	level %						
DTI	Level	Panel	level	35.1	2.6	31.1	34.9	39.8	Federal Housing Finance Agency
$DTI36$	$DTI \geq 36$	Panel	level %	48.1	9.9	32.6	47.5	65.5	Federal Housing Finance Agency
$DTI43$	$DTI \geq 43$	Panel	level %	23.5	9.3	9.8	22.9	40.0	Federal Housing Finance Agency
$\bar{K}$	Payment constraint	Series	level %	37.9	2.0	34.6	37.8	41.4	Author's calculations
B	Maximum loan amount	Panel	log-difference*100	1.9	5.1	-6.2	2.8	9.2	Author's calculations
$\hat{u}$	Disequilibrium	Panel	log-difference*100	0.2	15.2	-22.1	-0.6	27.6	Author's calculations

Correlation matrix

	P	W	R	DTI	$DTI36$	$DTI43$	$\bar{K}$	B	$\hat{u}$
P	1.00	0.12	-0.12	-0.05	-0.01	-0.08	-0.12	0.01	0.08
W	0.12	1.00	0.05	0.04	0.03	0.02	-0.01	0.29	0.05
R	-0.12	0.05	1.00	0.10	-0.15	0.10	-0.05	-0.07	0.19
DTI	-0.05	0.04	0.10	1.00	0.95	0.96	0.77	-0.06	0.60
$DTI36$	-0.01	0.03	-0.15	0.95	1.00	0.91	0.72	-0.06	0.51
$DTI43$	-0.08	0.02	0.10	0.96	0.91	1.00	0.81	-0.05	0.61
$\bar{K}$	-0.12	-0.01	-0.05	0.77	0.72	0.81	1.00	-0.08	0.66
B	0.01	0.29	-0.07	-0.06	-0.06	-0.05	-0.08	1.00	-0.11
$\hat{u}$	0.08	0.05	0.19	0.60	0.51	0.61	0.66	-0.11	1.00

Note: Variables are described in the text. The sample consists of quarterly data between 1996Q1 and 2021Q4 for 100 large cities in the United States.

Table 2: Disequilibrium Measure Encompassing Regressions

Estimated equation: $\Delta p_{it} = a_i + a_t + \alpha_1 \hat{u}_{1it} + +\alpha_2 \hat{u}_{2it} + \sum_{j=1}^{3} d_{1j} \Delta p_{it-j+1} + \sum_{j=1}^{2} d_{2j} \Delta b_{it-j} + e_{it}$

Disequilibrium Measure	$\hat{u}_{it}(b)$ (1)	$\hat{u}_{it}(y)$ (2)	$\hat{u}_{it}(y,r;unr.)$ (3)	$\hat{u}_{it}(y,r,k;unr.)$ (4)	$\hat{u}_{it}(y,r;rest.)$ (5)	$\hat{u}_{it}(b;30yr)$ (6)	$\hat{u}_{it}(b;T10)$ (7)	$\hat{u}_{it}(b;CCE)$ (8)	$\hat{u}_{it}(b;CDP)$ (9)
Measure in Column	-0.0381***	-0.0363***	-0.0334***	-0.0343***	-0.0365***	-0.0385***	-0.0362***	0.0000495	-0.0248***
	[0.00201]	[0.00223]	[0.00193]	[0.00237]	[0.00193]	[0.00211]	[0.00197]	[0.000145]	[0.00168]
RMSE	0.0147	0.0147	0.0148	0.0149	0.0147	0.0147	0.0147	0.0151	0.0148
		(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
$\hat{u}_{it}(b)$		-0.0506***	-0.0562***	-0.0454***	-0.0360***	-0.0956***	-0.0306*	-0.0384***	-0.0340***
		[0.00622]	[0.00517]	[0.00276]	[0.00914]	[0.0209]	[0.0142]	[0.00202]	[0.00274]
Measure in Column		0.0132*	0.0223***	0.0122***	-0.00205	0.0594**	-0.00733	0.000258	-0.00407*
		[0.00583]	[0.00525]	[0.00354]	[0.00883]	[0.0212]	[0.0136]	[0.000130]	[0.00169]
RMSE		0.0147	0.0147	0.0147	0.0147	0.0147	0.0147	0.0147	0.0147

Note: $*$, $**$, and $***$ denote significance at the 0.1, 0.05, and 0.01 levels, respectively. Models 1 through 9 use a single disequilibrium measure, noted in the column. Models 10 through 17 include the baseline estimate of $\hat{u}$—based on maximum loan amounts and estimated without augmented residuals—alongside an alternative measure, noted in the column. All models are estimated using un-augmented residuals. All disequilibrium measures except the CCE measure provide equilibrium correction as shown by estimates in models 1 through 9. Models 10 through 17 show the baseline $\hat{u}$ measure encompasses all others, as the sign and significance is maintained while others become statistically indistinguishable from zero or positive in sign.

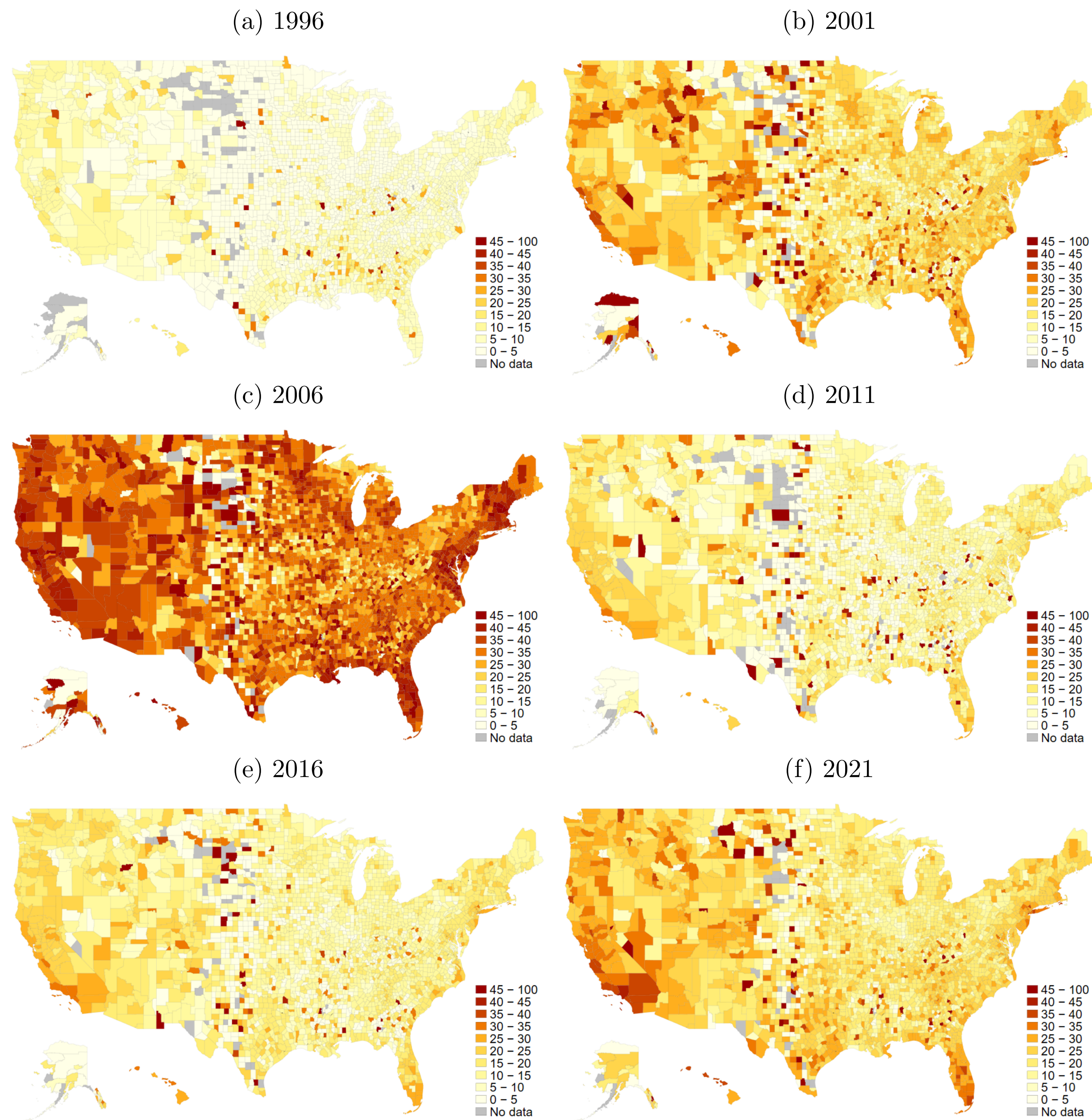
Table 3: Dynamic Models of House Prices

	Dependent Variable: House Price (quarterly, log-differenced)						
Model Number	[1]	[2]	[3]	[4]	[5]	[6]	[7]
DTI Formulation	$Share \geq 43$	Mean	$Share \geq 36$	$Share \geq 43$	$Share \geq 43$	$Share \geq 43$	$Share \geq 43$
$\hat{u}_{it}$	0.0338***	0.101***	0.0111	-0.00197	-0.0229***	0.0959***	0.0789***
	[0.00369]	[0.0201]	[0.00600]	[0.00486]	[0.00488]	[0.0112]	[0.0123]
$\hat{u}_{it} \times DTI\ measure$	-0.224***	-0.00376***	-0.0896***	-0.123***	-0.0337*	-0.362***	-0.300***
	[0.0133]	[0.000564]	[0.0117]	[0.0181]	[0.0137]	[0.0329]	[0.0344]
$\hat{u}_{it}^{-}$						-0.141***	-0.121***
						[0.0129]	[0.0145]
$\hat{u}_{it}^{-} \times DTI\ measure$						0.356***	0.241***
						[0.0473]	[0.0572]
Δp_{it-1}	0.132***	0.0284	0.0297	0.0282	-0.0561*	0.0141	-0.0722**
	[0.0294]	[0.0273]	[0.0275]	[0.0272]	[0.0266]	[0.0266]	[0.0263]
Δp_{it-2}	0.369***	0.330***	0.330***	0.331***	0.268***	0.317***	0.248***
	[0.0146]	[0.0162]	[0.0162]	[0.0162]	[0.0205]	[0.0160]	[0.0197]
Δp_{it-3}	0.348***	0.357***	0.356***	0.359***	0.338***	0.354***	0.328***
	[0.0243]	[0.0184]	[0.0185]	[0.0182]	[0.0170]	[0.0181]	[0.0173]
Δb_{it-1}	0.0292***	0.0301	0.0303	0.0311	0.0287	0.0293	0.0271
	[0.00361]	[0.0232]	[0.0233]	[0.0232]	[0.0199]	[0.0245]	[0.0201]
Δb_{it-2}	0.0335***	0.0118	0.0120	0.0125	0.0124	0.0124	0.0118
	[0.00288]	[0.0127]	[0.0127]	[0.0127]	[0.0127]	[0.0146]	[0.0130]
Time Period FEs	No	Yes	Yes	Yes	No	Yes	No
City FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CCE Controls	No	No	No	No	Yes	No	Yes
Observations	10200	10200	10200	10200	10200	10200	10200
RMSE	0.0161	0.0145	0.0145	0.0145	0.0137	0.0144	0.0136
F-stat (Δb_{it-j} coeffs sum = 0)	114.3	0.850	0.853	0.903	1.121	0.746	1.014
p-value (Δb_{it-j} coeffs sum = 0)	< 0.001	0.431	0.429	0.409	0.330	0.477	0.366
F-stat (each Δb_{it-j} coeffs = 0)	210.7	1.525	1.547	1.656	1.736	1.246	1.488
p-value (each Δb_{it-j} coeffs = 0)	< 0.001	0.220	0.217	0.201	0.191	0.267	0.225
Residual Correlation	0.180	-0.007	-0.006	-0.007	-0.008	-0.006	0.001

Note: $*$, $**$, and $***$ denote significance at the 0.1, 0.05, and 0.01 levels, respectively. Parameters presented are estimates of coefficients from OLS regressions. The sample is a balanced panel of quarterly data between 1996Q1 and 2021Q4. The variable p is a house price index, b is a maximum loan amount index, and $\hat{u}$ is a measure of disequilibrium from a fundamental house price estimated in auxiliary models. Parameters on $\hat{u}$ indicate reversion to long-run equilibrium, with larger (in magnitude) values indicating faster convergence. Parameters on $\hat{u} \times DTI$ indicate a speed of convergence associated with payment constraints. A negative superscript takes the value of the series when negative and 0 otherwise. CCE controls are means of left and right-hand side variables with loadings that vary by city (Holly et al., 2010). Residual correlations are the average of all two-city residual correlations within time periods. All correlations presented are significantly different than zero at the 1% level.

Appendix

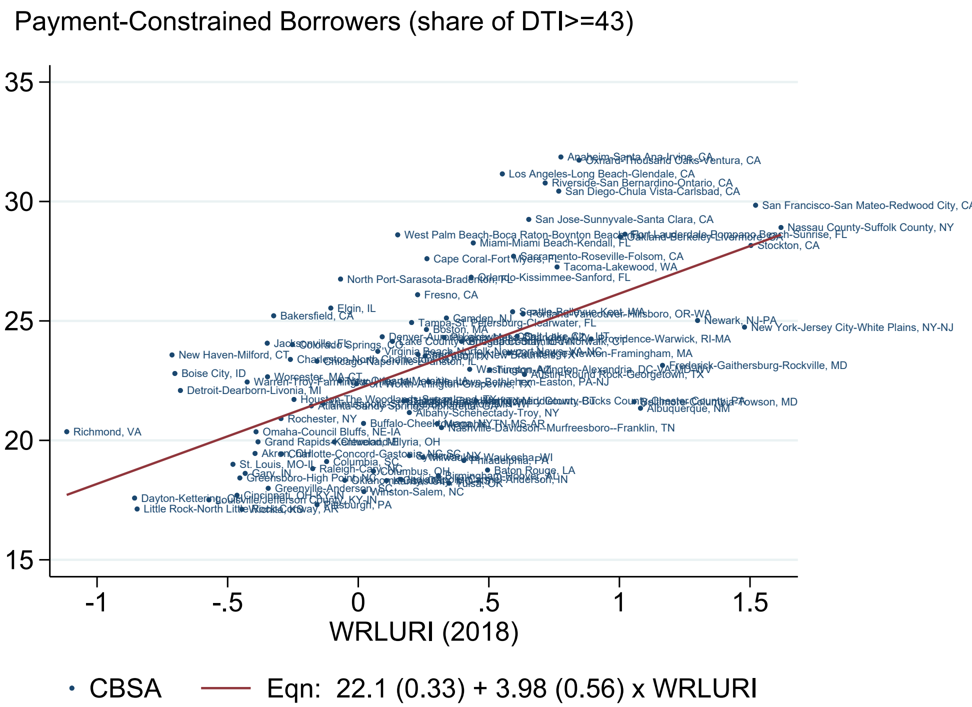
Figure A.1: Share of Enterprise Borrowers with $DTI \geq 43$



Sources: Internal FHFA data.

Notes: County values are the share of first-lien home purchase loans with a back-end debt service-to-income (DTI) ratio greater than or equal to 43%, averaged over the calendar year.

Figure A.2: Payment constraints and land use regulation



Sources and notes: DTI43 is calculated based on internal FHFA data as the share of purchase-money mortgage borrowers with back-end debt-service-to-income (DTI) ratios greater than 43% at origination, averaged across time periods for each city. The Wharton Residential Land Use Regulatory Index (WRLURI) is described by Gyourko et al. (2021). The sample consists of the 96 out of 100 cities with WRLURI values.

Table A.1: Long-Run Regression Estimates

CBSA Name	CBSA	BASE	CCE	CDP	CBSA Name	CBSA	BASE	CCE	CDP
Los Angeles-Long Beach-Glendale, CA	31084	0.78	-3.82	0.11	Bakersfield, CA	12540	0.47	1.76	-0.15
Honolulu, HI	46520	0.78	0.83	0.52	Pittsburgh, PA	38300	0.47	1.54	0.33
Austin-Round Rock-Georgetown, TX	12420	0.75	0.85	0.59	New Orleans-Metairie, LA	35380	0.47	0.57	0.23
Anaheim-Santa Ana-Irvine, CA	11244	0.74	3.92	0.19	Knoxville, TN	28940	0.47	-0.39	0.22
Boise City, ID	14260	0.68	3.84	0.10	Worcester, MA-CT	49340	0.46	3.86	-0.02
Miami-Miami Beach-Kendall, FL	33124	0.68	1.50	-0.03	Greenville-Anderson, SC	24860	0.45	1.76	0.24
San Diego-Chula Vista-Carlsbad, CA	41740	0.66	2.27	0.08	Charlotte-Concord-Gastonia, NC-SC	16740	0.45	-4.12	0.18
Philadelphia, PA	37964	0.66	4.53	0.34	Oklahoma City, OK	36420	0.44	0.32	0.29
Riverside-San Bernardino-Ontario, CA	40140	0.66	1.40	-0.18	Tucson, AZ	46060	0.44	1.45	-0.11
Oxnard-Thousand Oaks-Ventura, CA	37100	0.66	1.60	0.05	Minneapolis-St. Paul-Bloomington, MN-WI	33460	0.44	3.69	-0.02
Denver-Aurora-Lakewood, CO	19740	0.66	3.41	0.38	Wilmington, DE-MD-NJ	48864	0.44	2.54	0.08
Oakland-Berkeley-Livermore, CA	36084	0.65	1.47	-0.04	Camden, NJ	15804	0.44	6.43	0.02
Washington-Arlington-Alexandria, DC-VA-MD-WV	47894	0.65	2.60	0.24	El Paso, TX	21340	0.43	-0.90	0.23
San Francisco-San Mateo-Redwood City, CA	41884	0.64	0.34	0.30	Baton Rouge, LA	12940	0.43	1.09	0.29
West Palm Beach-Boca Raton-Boynton Beach, FL	48424	0.63	-1.26	-0.12	Raleigh-Cary, NC	39580	0.43	0.98	0.24
Fort Lauderdale-Pompano Beach-Sunrise, FL	22744	0.63	-0.88	-0.10	Syracuse, NY	45060	0.42	-0.09	0.23
Portland-Vancouver-Hillsboro, OR-WA	38900	0.63	1.26	0.26	Allentown-Bethlehem-Easton, PA-NJ	10900	0.42	1.39	0.03
Seattle-Bellevue-Kent, WA	42644	0.62	0.61	0.22	Las Vegas-Henderson-Paradise, NV	29820	0.41	-1.07	-0.58
Tacoma-Lakewood, WA	45104	0.61	0.81	0.07	Atlanta-Sandy Springs-Alpharetta, GA	12060	0.40	2.20	-0.02
Houston-The Woodlands-Sugar Land, TX	26420	0.61	0.35	0.47	Bridgeport-Stamford-Norwalk, CT	14860	0.40	1.96	0.03
Charleston-North Charleston, SC	16700	0.60	0.84	0.19	Kansas City, MO-KS	28140	0.40	-1.52	0.07
Nassau County-Suffolk County, NY	35004	0.60	0.81	0.12	Tulsa, OK	46140	0.40	-0.70	0.23
Tampa-St. Petersburg-Clearwater, FL	45300	0.59	-1.22	-0.07	Louisville/Jefferson County, KY-IN	31140	0.39	-0.08	0.19
Salt Lake City, UT	41620	0.58	5.70	0.29	Albuquerque, NM	10740	0.39	1.52	0.13
San Antonio-New Braunfels, TX	41700	0.58	-0.94	0.42	Grand Rapids-Kentwood, MI	24340	0.39	4.76	0.02
Phoenix-Mesa-Chandler, AZ	38060	0.58	-3.40	-0.11	New Haven-Milford, CT	35300	0.39	7.12	-0.01
Dallas-Plano-Irving, TX	19124	0.58	0.39	0.36	St. Louis, MO-IL	41180	0.39	0.28	0.07
San Jose-Sunnyvale-Santa Clara, CA	41940	0.57	0.66	0.20	Columbus, OH	18140	0.38	-2.87	0.11
New York-Jersey City-White Plains, NY-NJ	35614	0.57	1.87	0.17	Milwaukee-Waukesha, WI	33340	0.38	0.80	0.03
Frederick-Gaithersburg-Rockville, MD	23224	0.57	4.85	0.17	Birmingham-Hoover, AL	13820	0.38	-0.83	0.10
Sacramento-Roseville-Folsom, CA	40900	0.57	0.60	-0.16	Rochester, NY	40380	0.37	0.78	0.22
Nashville-Davidson–Murfreesboro–Franklin, TN	34980	0.57	4.83	0.31	Indianapolis-Carmel-Anderson, IN	26900	0.37	3.61	0.15
North Port-Sarasota-Bradenton, FL	35840	0.55	0.38	-0.19	Wichita, KS	48620	0.37	-0.93	0.17
Boston, MA	14454	0.54	1.76	0.15	Hartford-East Hartford-Middletown, CT	25540	0.36	3.06	0.08
Cape Coral-Fort Myers, FL	15980	0.54	0.59	-0.30	Omaha-Council Bluffs, NE-IA	36540	0.36	2.60	0.14
Orlando-Kissimmee-Sanford, FL	36740	0.54	-0.80	-0.18	Columbia, SC	17900	0.36	-0.56	0.12
Baltimore-Columbia-Towson, MD	12580	0.54	9.88	0.16	Little Rock-North Little Rock-Conway, AR	30780	0.35	0.82	0.21
Fort Worth-Arlington-Grapevine, TX	23104	0.54	-2.89	0.31	Gary, IN	23844	0.34	-0.14	0.09
Jacksonville, FL	27260	0.53	0.87	-0.06	Cincinnati, OH-KY-IN	17140	0.30	0.87	0.03
Richmond, VA	40060	0.52	1.67	0.16	Chicago-Naperville-Evanston, IL	16984	0.30	1.59	-0.15
Cambridge-Newton-Framingham, MA	15764	0.52	1.22	0.16	Winston-Salem, NC	49180	0.29	-0.72	0.07
Colorado Springs, CO	17820	0.51	0.23	0.18	Memphis, TN-MS-AR	32820	0.29	-1.11	0.02
Fresno, CA	23420	0.51	2.59	-0.16	Greensboro-High Point, NC	24660	0.29	0.90	0.06
Providence-Warwick, RI-MA	39300	0.51	0.13	0.00	Dayton-Kettering, OH	19430	0.24	3.08	-0.06
Virginia Beach-Norfolk-Newport News, VA-NC	47260	0.50	5.37	0.15	Warren-Troy-Farmington Hills, MI	47664	0.23	0.22	-0.14
Buffalo-Cheektowaga, NY	15380	0.50	2.27	0.36	Elgin, IL	20994	0.21	0.08	-0.27
Montgomery County-Bucks County-Chester County, PA	33874	0.49	4.05	0.17	Akron, OH	10420	0.21	0.21	-0.06
Newark, NJ-PA	35084	0.49	-1.72	0.05	Lake County-Kenosha County, IL-WI	29404	0.19	-0.47	-0.19
Albany-Schenectady-Troy, NY	10580	0.49	-4.32	0.25	Cleveland-Elyria, OH	17460	0.18	2.48	-0.11
Stockton, CA	44700	0.48	-1.78	-0.41	Detroit-Dearborn-Livonia, MI	19804	0.14	5.43	-0.37

Estimates are from city-by-city estimates of β_{i1} in $p_{it} = \beta_{i0} + \beta_{i1} b_{it} + u_{it}$. The BASE model estimates this model as written. The CCE model includes the common correlated effects controls from Holly et al. (2010). The CDP model includes the common dynamic process control from Teal and Eberhardt (2010).