Regional Divergence and House Prices*

Greg Howard[†] Jack Liebersohn[‡]

October 12, 2022

Abstract

We document a new fact: regional divergence, the rate at which rich states grow faster than poor states, explains most U.S. house price movements since 1939, including the post-2000 boom-bust-boom cycle. An industry-share instrument provides evidence the relationship is causal, implying the location of economic growth affects national house prices. We propose a model to learn why regional divergence and house prices are related. In the model, high interstate inequality raises rents on average because relative demand for living in a high-income state increases and housing supply in low-income states is elastic. Regional divergence leads to higher expected future interstate inequality, which implies higher expected future rents, and therefore, higher current house prices. The model accurately predicts rents since 1929, which are quite different than prices, as well as cross-sectional moments of prices, rents, construction, and migration.

JEL Codes: R31, G12, E22
Keywords: regional inequality, expectations, house price-rent ratio

*We would like to thank Hansen Shao for his research assistance, and Jan Brueckner, Mike Eriksen, Carlos Garriga, Dan Greenwald, Nina Karnauk, Ye Li, Victor Lyonnet, Yueran Ma, Raven Molloy, Dejanir Silva, David Thesmar, seminar and conference participants at the St. Louis Federal Reserve, the Federal Reserve Board of Governors, the University of Cincinnati, Chicago Federal Reserve, the Upjohn Institute, SED, the Econometric Society, AREUEA, the University of California—Irvine, and the Bank of Canada for their comments. All errors are our own.

[†]Corresponding author. University of Illinois, Urbana-Champaign, glhoward@illinois.edu. 1407 W Gregory Dr, Urbana, IL 61801.

[‡]University of California, Irvine, cjlieber@uci.edu.

Housing is a large part of most households' portfolios, and housing is central for fiscal and monetary policy discussions, but the determinants of house price movements are still debated. We argue that regional divergence, the rate at which rich states are growing relative to poor states, has a causal impact on house prices and is able to explain much of house price movements since World War II. The mechanism we propose matches many other features of the data, including the time series of rents, the cross-section of house prices, the location of construction, and the direction of internal migration. In addition, it suggests a new role for the effects of monetary policy which clarifies the weak empirical link between interest rates and house prices (Glaeser, Gottlieb and Gyourko, 2012).

Regional convergence and divergence are growing topics of study in economics, largely because convergence has significantly slowed down in recent decades.[1] Using a common measure of divergence based on ten-year state-level average personal income growth rates, we show that house prices and regional divergence are even more correlated than previously recognized.[2] Not only is the long-term trend similar, but many fluctuations in regional divergence and house prices coincide as well, dating back to World War II and including the boom-bust-boom pattern of the last twenty years. Based on the literature's findings that industry growth is a significant driver of divergence, we use an industry-based shift-share instrument to provide evidence that the relationship between regional divergence and house prices is causal. Intuitively, when industries concentrated in rich states grow faster than other industries,

[1]Barro and Sala-I-Martin (1991) argued that regional convergence was fairly steady, with short-term deviations due to industry fluctuations. However, since that paper was written, convergence has been much slower (Moretti, 2013; Giannone, 2017).

[2]Ganong and Shoag (2017) prominently note that the convergence slowdown has coincided with a rise in house prices. They present a story in which increased housing regulations and decreasing supply elasticities can explain higher house prices and more divergence. Our paper emphasizes a different causal direction, and we see no reason that both channels cannot be present in the data. They are focused much more on the long-term changes rather than the fluctuations that have been the interest of the macro literature in recent years.

divergence is high. We show such movements have an effect on house prices using the identification strategy of Borusyak, Hull and Jaravel (2022) and the local projection methods of Jordà (2005).

Why do movements in divergence cause movements in house prices? The mechanism we present treats prices as the present value of future rents (as in Poterba, 1984) and considers specifically what determines rent expectations. When the income gap between rich and poor areas is larger, relative demand to live in rich areas is higher, leading to a larger gap in rents between poor and rich areas. Since housing supply is more elastic in poor areas, rents in poor areas are stable and rents in rich areas are higher. We model beliefs about divergence as backward-looking, i.e., people expect the current level of divergence to persist. Therefore, greater divergence implies expectations of higher future regional inequality, higher future average rents, and therefore higher house prices in the present.

We develop a parsimonious model that captures this mechanism. The model has four ingredients that build on existing research on housing and rental markets: (1) house prices are the present value of future rents; (2) people are mobile across space, defining an equilibrium cross-sectional relationship between income and rent; (3) poor areas have high housing supply elasticity; and (4) expectations of future regional divergence reflect the recent past.

Of these, assumption (4) is the most novel, and we devote a portion of the paper to explaining why the recent past determines agents' expectations. First, we establish that regional divergence helps explain a significant portion of state-level income growth. While not shocking given the existing literature on divergence, it shows that there is an important common component across states that helps predict income movements. Second, we show that divergence is both fairly noisy and highly persistent in the data, justifying why agents ought to pay attention to the recent past for predicting the future, but also ought to look at several years of data. Finally, we show that expectations data from the Michigan Survey of Consumers match what we would expect based on such an assumption.

After we feed in the data on state-level income, the model succeeds in matching many facts about house prices and rents. In the time series, we show that the model generates trends and fluctuations in rents and house prices that match the data closely. The time series of house prices and of rents look quite different from one another. We believe ours is the first paper that has even attempted to match this long of a time-series between rents and house prices.[3]

Matching the price-to-rent ratio has been a challenge in the literature. Several papers have made the assumption that the rental and owner-occupied housing markets are segmented in order to match the volatility in the price-to-rent ratio (e.g. Greenwald and Guren, 2021). A challenge to the segmentation story is that Begley, Loewenstein and Willen (2019) show that the price-rent ratio for just rental homes exhibited the same pattern as the overall market, which is hard to explain using segmented markets.[4] Therefore, an additional contribution is that our theory can explain the major movements in both rents and prices—and hence the price-rent ratio—without making the segmented markets assumption. By explaining the price-rent ratio without segmented markets, this paper shows that expectations, in addition

[3]While the model can match the trends of house prices and rents, we are more focused on the fluctuations because of concerns in the literature that the long-term trends in the data may be biased. For example, Crone, Nakamura and Voith (2010) suggest much of the rent series is downward biased from non-response bias. Similarly, there are questions as to whether house prices as measured from 1953-1975 suffer from bias because they are measured using housing sales that qualify for certain mortgages which are capped at certain dollar amounts. House prices before 1953 are even more poorly measured, based on newspaper listings in five cities.

[4]The reason this is a challenge for the segmentation story is that substitution towards owner-occupied units would not explain why the price-rent ratio for rental homes increased. Hence, even if markets were entirely segmented, there would still be a mystery surrounding the price-rent ratio that our theory is able to explain.

to fundamentals, play an important role in house price determination.[5]

Our analysis focuses on divergence at the state level rather than at the city level because state data allows us to extend the analysis back to World War II. Matching the long time series is a stronger test of our theory than focusing solely on the volatile recent years. Typically, other papers that focus on recent house price movements do not try to match such a long time period. At the same time, in matching the long time series of prices and rents the paper offers insights on recent movements in house prices. In Appendix A.2, we show robustness to measuring divergence in a variety of ways, including by CBSA.

The model is designed to explain the history of house prices in the United States, but we can further evaluate it by looking at a series of non-targeted cross-sectional relationships. First, the model is able to explain why the cross-sectional relationship between house prices and income changes over time, while the cross-sectional relationship between rent and income is relatively constant. Intuitively, when divergence is high, the income premium in high-income areas is expected to last longer, which means the rent premium in these areas is expected to last longer as well. This means that the cross-sectional relationship between incomes and prices should be greater when divergence is high than when divergence is low. In contrast, divergence should not affect the relationship between rents and incomes, which is determined by current incomes rather than expected future incomes.

Second, a well-studied fact about the U.S. housing market is that house prices in less-elastic, higher-income areas move more than one-for-one when national house prices change, whereas prices in more elastic, lower-income areas move by less than one-for-one with the national index (Mian and Sufi, 2009; Glaeser, Gyourko and Saiz,

[5] Kaplan, Mitman and Violante (2019) also assume non-segmented markets. They match the housing boom and bust by assuming an exogenous change in expectations over the future demand for housing.

2008; Guren, McKay, Nakamura and Steinsson, 2021).[6] Our model can match the differential sensitivities of local house prices to the national aggregate.

The model provides two main insights for understanding the history of house prices. First, local demand shocks are crucial for explaining cross-sectional variation in house prices. While supply elasticity plays a role in our theory, it cannot explain local price variation alone. Second, fluctuations in the price to rent ratio can be explained using a model of expectations based on fundamental shocks. This is an alternative to assuming segmented housing markets, as in much of the prior literature.

There are two classes of theories in the house price literature that attempt to explain movements in house prices along with the large cross-sectional price differences. The first class of theories is that there are large national housing demand changes, and that heterogeneous price changes are due to difference in the elasticity of housing supply. This class of theories is prominent in the literature due to the influential work of Mian and Sufi (Mian and Sufi, 2009, 2011; Mian, Rao and Sufi, 2013), and it includes much of the debate on the roles of expectations versus credit in the recent boom and the bust.[7,8]

[6]This is distinct from the fact that *within-city*, lower-income neighborhoods are more sensitive to house prices (Mian and Sufi, 2009). The fact we are trying to match is about sensitivity *across* regions.

[7]We discuss our the expectations literature in more detail below. Important papers that have argued for the importance of a credit channel include Ambrose and Thibodeau (2004), Favilukis, Ludvigson and Van Nieuwerburgh (2017), Greenwald (2018), Landvoigt (2017), Di Maggio and Kermani (2017) and Liu, Wang and Zha (2019). Justiniano, Primiceri and Tambalotti (2019), Mian and Sufi (2019) and Jacobson (2019) consider the interaction of credit and expectations. Future research could integrate the credit-focused and regional equilibrium approaches along the lines of Lamont and Stein (1999).

[8]One of the key assumptions in Kaplan et al. (2019) is that rental and owner-occupied housing are substitutable, which we adopt here. This has been controversial because relaxing this assumption allows for price-rent fluctuations due to people choosing owner-occupied housing instead of rental housing (Greenwald and Guren, 2021). Regardless of the substitutability, Begley et al. (2019) show that rental properties had just as big of an increase in price-rent ratios during the 2000s boom as owner-occupied housing. Consistent with this finding, our model predicts large movements in price-rent ratios through changing expectations of future rents, not through substitution between owner-occupied and rental housing.

The second class of theories posits that there are varying local demand shocks and that house price movements are best-explained by shifting demand for specific locations. Sometimes these theories are thought of as more "fundamentals-based," and as such, big swings in house prices can be discrediting. One of the best examples of a paper in this literature is Himmelberg, Mayer and Sinai (2005), which was published at the height of the housing boom and argued that prices were in line with fundamentals. Another prominent paper in this class of models, Van Nieuwerburgh and Weill (2010), considers the long-term increase in house price dispersion, but does not propose a theory of fluctuations.[9] Subsequent to our paper, research by Chodorow-Reich, Guren and McQuade (2021) argues, much like us, that variation in the price-to-rent ratio in the 2000s can be explained with a model of expectations rather than assuming segmented markets.

Our paper argues primarily in favor of this second class of theories, while including an important role for supply elasticity as in the first class. By modeling expectations based on recent regional divergence, our theory provides a new rationale for the large swings. The goal of our model is to match the long time series of prices and rents, but it also provides a new perspective on the more recent period. For example, because the growth rate in rich states declined in the mid-2000s—largely due to the temporary slow-down of services growth—it caused house prices to fall significantly. Our paper gives a mechanism for "fundamental"-based theories to still exhibit large swings.

Another way we contribute to this second class of theories is to explain the location of construction and migration with the help of insights from the first class of theories.

[9]A prominent example of a paper that provides a rationale for differing location demand is Gyourko, Mayer and Sinai (2013), which posits that higher income inequality can increase the demand for "superstar" cities. While this has some similarities to our paper, it focuses on inequality overall, not regional inequality, which is our focus. Given that the regional divergence we focus on is driven by sector-specific growth, and not overall inequality, we think these are two separate channels. Controlling for measures of income inequality does not do much to explain house prices in Table 1.

National demand shocks combined with differential housing supply elasticities imply more construction in low-income housing-supply-elastic areas.[10] Differential demand shocks, our class of theories, imply that construction and net migration should be higher in high-income inelastic areas. We show that data on construction and migration correspond more closely to our theory.[11,12]

We also contribute to the literature on expectations in housing markets, which has been shown to be central using a variety of methodologies, but for which the fundamental causes of the change in expectations are still a matter of debate. Our contribution is to point out that regional divergence matters for expectations.[13] In a sense, regional divergence is the missing ingredient that explains why expectations change.[14]

A large literature discusses the role of expectations in the mid-2000s housing boom.[15] This paper's goal is to understand the long history of prices and rents, but

[10]There is a high correlation between housing supply elasticities and income, as we show in Figure 6, and is documented in Saiz (2010).

[11]We make two other contributions to this literature, which we previously discussed. First, we present time-series evidence of causality using our shift-share instrument. Second, we show that the model is consistent with the data over a much longer time series, both because we go further back in time (to World War II as relates to house prices, and to 1929 as it relates to rents), and further forward in time, as much of the previous work was done before the housing bust.

[12]This prediction also distinguishes our findings from Ganong and Shoag (2017), which posits a relationship between house prices and divergence, but is focused on long-term trends and argues for a different mechanism than we do.

[13]Research has also found that changes to fundamentals, such as the ones we study, can cause large changes in expectations even if the changes to fundamentals are small. One mechanism for this, which has support from survey data, is extrapolative expectations (Armona, Fuster and Zafar, 2019; Glaeser and Nathanson, 2017). Another possible explanation is based on social or learning dynamics (DeFusco, Nathanson and Zwick, 2022; Burnside, Eichenbaum and Rebelo, 2016; Adam, Kuang and Marcet, 2012). Rozsypal and Schlafmann (2017) and Nagel (2012) show evidence that expectations are influenced by recent income experience and Kwan and Cotsomitis (2004) demonstrates that it does carry over into real behavior. We model the transmission of the fundamental to expectations in a reduced form way. We discuss this issue more in Section 3.

[14]We view our paper as complementary to the large literature that emphasizes how expectations are formed, but that does not focus on the changes to the initial fundamental. Here, we adopt a very simplistic backward-looking expectations assumption and focus on the initial change in the fundamental.

[15]Papers that argue for an expectations channel include Kaplan et al. (2019); Burnside et al. (2016); Shiller (2007); Piazzesi and Schneider (2009); Foote, Gerardi and Willen (2012); Gelain and

the 2000s boom and bust is an example that illustrates our mechanisms. As Glaeser et al. (2012) put it,

> Why were buyers so overly optimistic about prices? Why did that optimism show up during the early and middle years of the last decade, and why did it show up in some markets but not others? Irrational expectations are surely not exogenous, so what explains them?

Our model draws attention to high divergence in the early 2000s as a force that helped raise prices.

Finally, we contribute to the literature on the relationship between house prices and interest rates (Taylor, 2007; Glaeser et al., 2008; Jordà, Schularick and Taylor, 2020). Our model has a different role for interest rates than the rest of the literature. In our model, the effect of interest rates is not always the same sign. Low interest rates put a higher weight on future income, so in times of expected divergence, low rates raise house prices, but in times of expected convergence, low rates lower house prices. Moreover, relevant to the recent experience, low interest rates make house prices more sensitive to divergence, increasing volatility.

In the next section, we show that regional divergence, as commonly measured, and house prices are highly correlated, and that there is a causal channel from divergence to house prices. In Section 2, we present a theory of why this channel exists. In Section 3, we defend the assumptions of our model. In Section 4, we show that many non-targeted predictions of the model hold in the data and that the construction and migration data are more supportive of our theory than other theories in the literature. Section 5 discusses the role of interest rates and Section 6 concludes.

Lansing (2014); Adelino, Schoar and Severino (2013); Nathanson and Zwick (2018); Glaeser and Nathanson (2017); and Ben-David, Towbin and Weber (2019).

1 Time-Series Evidence

We begin by establishing reduced-form facts about the relationship between regional divergence and housing prices. First, we use time series regressions to show that regional divergence is a quantitatively important predictor of house prices in the United States. Next, we instrument for divergence using the heterogeneity in industry shares by location. Our instrument provides evidence that changes in divergence cause changes in house prices.

Throughout the paper, our primary measure of divergence is the estimated $\hat{\kappa}_t$ from the following regression:

$$\frac{1}{10}(\log w_{i,t} - \log w_{i,t-10}) = \kappa_t \log w_{i,t-10} + \lambda_t + \epsilon_{i,t} \tag{1}$$

where i indexes states, t indexes years, and w_{it} is the state per capita personal income data from the Bureau of Economic Analysis for the 48 continental states and the District of Columbia.[16] λ_t is a year fixed effect. While we run this regression all at once, it is identical to running separate regressions to calculate divergence in each year. Hence, the left-hand side of the regression is the average ten-year growth rate of personal income per capita, and κ_t is the regression coefficient on lagged log income per capita.

Figure 1 shows the relationship between state-level income growth and the lagged level of income in two years, 1950 and 2014. The divergence measure for each year, κ_t, is the slope of the fit line. Divergence in 1950 is one of the lowest in the sample — the line is very negative, with lower-income states growing much faster than higher-income ones. By contrast, in 2014, the line is nearly flat (the overall level of income

[16]We exclude Hawaii and Alaska because there is less mobility to and from those states, because Alaska's personal income is noisy, and because they enter the sample part-way through. Including them in the measure of divergence does not substantially change the results in Section 1.

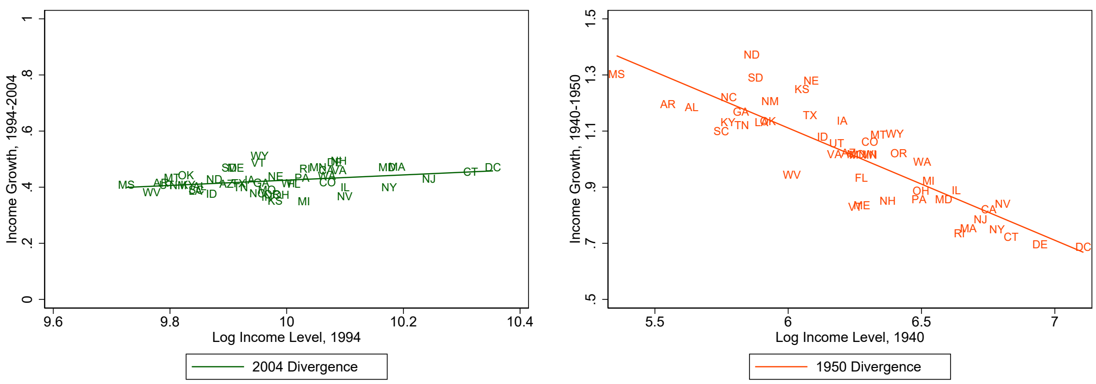


Figure 1: **Measuring Divergence: Income Growth versus Initial Income Level, 1950 and 2014.** Regional divergence in a given year is measured by regressing the 10-year average growth rate of income on the ten-year lagged log of income.
Source: Income at the state level is the per capita personal income as measured by the Bureau of Economic Analysis (BEA).

growth is also lower). This means that incomes grew roughly as quickly in lower- and higher-income states.

In Figure 2, we show the time series of divergence–the κ_t from equation (1)–and the time series of real house prices. We see in the figure that divergence is usually negative, but varies significantly over time. What this means is that state incomes neither converge at a steady rate, nor are they independent of the initial income level. Instead, state incomes are best characterized as converging in some time periods, and staying similar or even diverging at other times.[17]

1.1 Quantifying the Divergence-House Price Relationship

Our first result is that divergence explains a large percentage of the variation in house prices. Comparing the two lines in Figure 2, it is apparent that the two lines are highly correlated: they both trend upward, and many of the fluctuations are similar.

[17]Section 3.1 quantifies how much better the state income process is characterized when we allow for time-varying divergence than if we assume it is fixed.

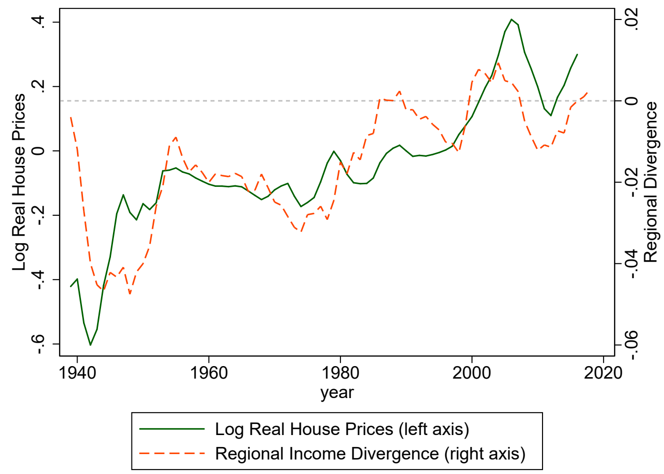


Figure 2: **Regional Divergence and Aggregate House Prices.** Regional divergence in a given year is measured by regressing the 10-year average growth rate of income on the ten-year lagged log of income (it is a backward looking measure). *Source:* House prices come from Knoll et al. (2017) and are deflated by CPI. Income at the state level is the per capita personal income as measured by the Bureau of Economic Analysis (BEA).

Column (1) of Table 1 shows the regression of house prices on the divergence measure from equation (1).[18]

$$\log \text{Real National House Prices}_t = \beta \hat{\kappa}_t + \epsilon_t$$

The R^2 of the divergence-house price relationship is economically large; divergence explains over half of the variation in house prices. Column (2) adds controls for a variety of potential determinants of house prices that have been considered in the literature. We include controls for log real GDP per capita, the 10-year treasury

[18] In order to test this relationship and figure out a sense of the magnitude, the first step is to establish that the series are co-integrated. Tests of co-integration are able to reject the null hypothesis of no co-integration at the 5 percent level. The Engle and Granger (1987) test, with two lags, shows the residuals of the regression of house prices on divergence are stationary (we use the critical values from MacKinnon (2010) and run the test using Schaffer (2010)). The Johansen (1995) trace test, also with two lags, can reject that there are zero co-integrated relationships. Both were run without a trend term. With a trend term, we cannot reject a hypothesis that both series are stationary.

rates from Jordà, Schularick and Taylor (2015), the construction material producer price index, and the income share of the bottom 50 and top 1 percent, as calculated by Alvaredo, Chancel, Piketty, Saez and Zucman (2017). The coefficient on house prices remains large and statistically significant, and the R^2 increases, but only to a small extent. In regressions containing only the control variables and excluding divergence, the R^2 is only 0.3, implying that divergence explains about 47% of the residual variance after controlling for these variables.

1.2 Industry Composition Instrument

Next, we use an instrumental variables strategy to estimate the effect of divergence on house prices. Ordinary least squares might fail to identify the causal effect of divergence on house prices because of an omitted variable, such as housing supply policy changes (Ganong and Shoag, 2017), or reverse causality, if house price changes cause differential consumption patterns across space (Mian et al., 2013).

Following Barro and Sala-I-Martin (1991), we take the stand that industry-specific shocks are one of the driving forces of regional divergence. For industries concentrated in high-income areas, we would expect their growth to cause regional divergence, whereas for industries in low-income areas, growth would cause regional convergence.[19] Using this logic, we can predict regional divergence by combining data on industries' share of local income with data on their average growth rates at the national level. We then use our predicted divergence to trace out the effects of divergence on house prices at the national level.

Our measure of national industry growth rates is based on data provided by the BEA at the 2-digit industry level. For each state, we multiply the share of each

[19] Giannone (2017), Acemoglu and Restrepo (2020), and Eckert, Ganapati and Walsh (2020) also emphasize the role of technology in differential regional growth.

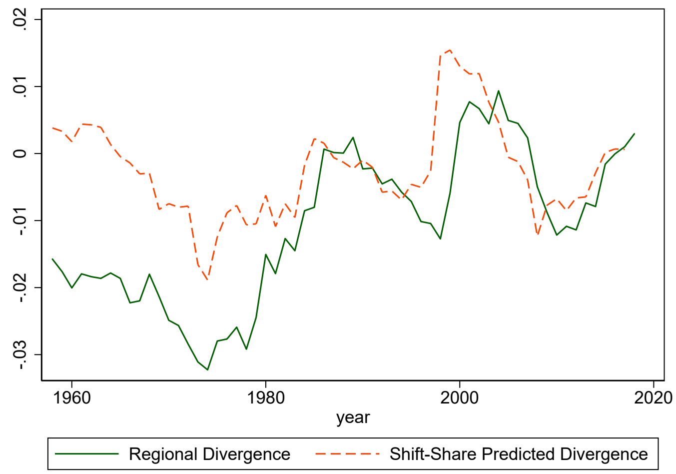


Figure 3: **Industry-Predicted Divergence and Divergence.** Industry-Predicted Regional Divergence is based on 2-digit SIC/NAICS industry GDP per employee growth, and industry shares in different states. Divergence is based on the growth of personal income.
Source: BEA and calculations described in the text.

industry in the state's personal income with the industry growth rate as measured by changes in GDP per employee at the national level, both using data from the BEA. We then construct a divergence measure, not based on actual state GDP per capita growth, but on this expected growth measure, similar to Bartik (1991).[20]

A recent literature studying shift-share research designs has laid out two sets of assumptions for such an identification strategy to be valid, based either on the exogenous assignment of industry shares (Goldsmith-Pinkham, Sorkin and Swift, 2020) or exogenous shocks to industry growth rates (Borusyak et al., 2022). We think that

[20]Similar results are obtained using changes in personal income per employee at the national level, but this is available for a smaller number of years. Regional employment is only available back to 1969, while industry GDP per capita is available in years prior to that. So for data before 1979, we use the share of employment in 1969 as the share, and GDP growth rate per capita as the shift. We use the ten-year lagged employment share until 1997, when SIC-basis industry data ends. For 1997-2017, we use NAICS basis industry data, holding consumption shares fixed at 2001 levels from 1997-2001 since personal income by NAICS industry begins in 2001. Appendix C.5 discusses the creation of this measure in more detail. In Appendix Figure A18 we also construct the instrument in a variety of ways, such as by using GDP shares instead of personal consumption shares, and show that the time series are quite similar.

Table 1: Effect of Divergence on House Prices

	(1) House Prices	(2) House Prices	(3) House Prices	(4) House Prices	(5) House Prices	(6) House Prices	(7) House Prices
Divergence	10.10***	7.428***	10.62**	8.743***	8.221***	11.24***	11.42***
	(1.796)	(1.073)	(3.264)	(1.827)	(1.966)	(1.615)	(1.761)
Log Real GDP/Cap		0.842***			0.232	0.430	0.411
		(0.246)			(0.373)	(0.333)	(0.349)
Real 10-Year Treasury		0.288				0.0202	0.00767
		(0.572)				(0.696)	(0.711)
Construction Material Price		0.774***				0.867***	0.872**
		(0.222)				(0.261)	(0.265)
Income Share of Bottom 50 Percent		-1.332				-1.270	-1.267
		(1.783)				(1.932)	(1.946)
Income Share of Top 1 Percent		-1.639				-0.959	-0.927
		(1.056)				(0.999)	(1.016)
R^2	.52	.63					
Year Controls	None	Spline	None	Cubic Spline	Cubic Spline	Cubic Spline	Cubic Spline
Specification	OLS	OLS	IV	IV	IV	IV	IV: No RE/Finance
Kliebergen-Paap F-stat			15.14	46.83	33.17	22.56	18.74
Observations	78	56	56	56	56	56	56

Standard errors robust to heteroskedasticity and autocorrelation (3 lags) in parentheses.
The cubic spline used has 5 knots. Divergence is instrumented using the industry-implied divergence, lagged by 3 years.
In Column (7), the industry-implied divergence excludes construction, real estate and finance.
$^{+}$ $p < .1$, * $p < .05$, ** $p < .01$, *** $p < .001$

the assumptions in Borusyak et al. (2022)—exogenous industry shocks—are more appropriate for our setting.[21] Under the Borusyak et al. (2022) assumptions, industry shares do not have to be exogenous across regions; for example, the concentration of the high-tech industry in low-elasticity areas would not present a problem for us.

Borusyak et al. (2022) provide ways to verify the validity of the assumptions behind our shift-share design. A critical one is a falsification test showing that the instrument does not predict lagged changes in the outcome. Corresponding to that, our local projection allows for a pre-trends test, akin to what they suggest.

In addition, Borusyak et al. (2022) emphasize the importance of sensitivity tests to variables that might be correlated to the shocks. In our case, it is important to

[21]Note that this assumption only matters for industries which are concentrated in either high- or low-income parts of the country, since industries which are equally large everywhere have no effect on divergence.

Further, under these assumptions, there is no need to construct the instruments using a leave-one-out methodology, as the plausible exogeneity is due to the randomness of which industries are growing faster.

test whether controlling for time series confounders, i.e. omitted variables that might be correlated to both the instrument and house prices, changes our estimates. The literature has relatively little guidance on what confounders might be correlated to the instrument, so we focus on variables that are argued to be correlated to house prices.

Finally, Borusyak et al. (2022) also emphasize clustering errors at the industry-level rather than the geographic level. Our approach is even more conservative, because we only have one observation per year. We have one observation per year, so we use HAC standard errors with a lag of three years for our specifications.

The time series of industry-predicted divergence is plotted in Figure 3. Two things stand out about this graph. The first is that industry growth is able to explain many of the changes in regional divergence. The second is that the changes predicted by industry growth have smaller fluctuations and lead the actual divergence line by a few years, perhaps due to the time it takes for demand to spillover into other sectors (Nakamura and Steinsson, 2014; Howard, 2020; Bartik and Sotherland, 2019).[22] The similarity of actual divergence to industry-predicted divergence supports our assumption that industry shocks are one of the main drivers of actual divergence. The smaller fluctuations in the industry-predicted series imply that local multipliers play a positive but quantitatively small role in magnifying local fluctuations.

In Columns (3)-(7) of Table 1, we use the instrument to test the causal relationship between regional divergence and real house prices. We instrument divergence with the industry-caused divergence, lagged three years. With a three-year lag, the first-stage F-stat is over 15, suggestive that it is a strong instrument.[23] The relationship

[22]A third thing to note would be that the industry-predicted divergence does not feature an upward trend, as does actual divergence. This is mainly an issue for the relevance of the instrument. In most of the specifications, we include controls for time-trends, so this is not a problem, but note that in Column (3) of Table 1, which does not feature a time trend, the instrument is weaker.

[23]The results are robust to a four-year or five-year lag, which yield similar results.

is statistically significant at the one percent level.

One potential threat to our identification is the possibility of omitted variables that are correlated to both our instrument and house prices. To check the robustness of our causal claim, we add controls to our regression, corresponding to the sensitivity analysis in Borusyak et al. (2022). First, we include a cubic spline, with five knots in Column (4). We also control for log real GDP per capita in Column (5). Column (6) adds the remaining control variables considered in Column (2). Our estimate remains fairly stable throughout.[24]

One way our identifying assumption could fail is if one industry's (e.g. the construction sector's) growth was correlated with shocks to housing demand; and at the same time, if that industry was a higher share of personal income in higher-income regions. If this were the case, divergence could spuriously be associated with house price increases, since an increase to housing demand would increase house prices and also cause that sector to grow, which in turn would increase regional divergence, causing the two series to be correlated. To deal with this concern, we show that fluctuations in the predicted divergence measure remain very similar if we exclude the construction, real estate and financial sectors (shown in Figure A20 of the Appendix).[25] In Column (6) we use this measure in place of the instrument, and the results are unchanged.

A side benefit to our shift-share strategy is that we can tell which industries are responsible for the increase in divergence. We selectively "turn off" each industry's

[24]The fact that the IV and OLS estimates are the same could reflect that multiple biases cancel out (e.g. a positive bias of house prices raising divergence through aggregate demand and a negative bias from house prices lowering the ability to agglomerate in rich cities).

Interestingly, only one of these controls is significant: the price of construction materials. This is largely because during the one period in which prices rose and divergence did not, the early 1980s, was a time in which construction materials has a large boom and bust. We discuss this more in Section 4.

[25]The reason is that real estate is a tiny share of personal income, while construction makes up roughly the same fraction of income in all parts of the U.S. and so shocks to these sectors have little effect on divergence overall. Finance has a small positive effect on divergence since it is concentrated in higher-income regions.

contribution to national divergence by setting the growth rate of these industries equal to the growth rate of average incomes, and recalculating predicted divergence. When we do this, we find that the industries most responsible for the rise in divergence right before the 2000's house price boom are professional services—information technology, finance and insurance, professional and scientific services, business services, etc.[26] These industries grew faster than the national average during this time and are concentrated in high-income regions. Setting their industries' growth to the national average reduces the increase in predicted divergence between 1995 and 2000 from 0.18 log points to 0.10 log points, as shown in A19 in the Appendix. Manufacturing, oil/mining, agriculture, and other services all play a smaller role in explaining the remainder of the boom. Before 1995 and after about 2010, professional services are not important for explaining divergence overall, and in general, we find that divergence is explained by different industries at different times.[27]

1.3 Impulse Responses

In order to check the exogeneity of our instrument, we also undertake an alternative approach to the time series analysis. We run a local projection to generate an impulse response of a change in the industry-driven divergence on measured divergence and house prices. Critically, this allows us to look at pre-trends of house prices that provides a falsification test along the lines suggested by Borusyak et al. (2022).

[26] We define this to be NAICS codes 51-52 and 54-71; and SIC codes 62-65, 67, and 73-86; or the equivalent BEA codes from each year.

This finding is consistent with Eckert et al. (2020), who argue that skilled scalable services are responsible for the decline in regional convergence.

[27] The increase after 2010 is driven by a mix of sectors, particularly "Mining, quarrying, and oil and gas extraction" and "Agriculture, forestry, fishing and hunting". If divergence were always explained by growth rates in any particular industry, we might worry that this industry has some special relationship to housing demand shocks.

We estimate the following local projection:

$$\log y_{t+s} - \log y_{t-1} = \beta_s \Delta \text{Industry Divergence}_t + \gamma X_t + \epsilon_t \tag{2}$$

where y is the outcome of interest, e.g. house prices, ΔIndustry Divergence is the one-year change in the previously-described measure, and X is a vector of controls. In our baseline, we include two lags of ΔIndustry Divergence.

As before, the identifying assumption is that shocks to the shift-share time series are orthogonal to any concurrent or future innovations in the time series of house prices that are not caused by changes in divergence

The results of this local projection are presented in Figure 4, with our measure of actual divergence and house prices as the two major outcomes. There is a statistically significant increase in both series. Even more importantly, there is no significant change in the five years prior to the shock. If anything, the statistically-insignificant pre-trend on house prices is in the wrong direction.

In Appendix Figure A1, we show sensitivity analysis for the previous result. As discussed in the previous section, one possible violation of the identification assumption is that housing demand is directly associated with certain industries, i.e. construction, real estate or finance. We show that the results do not vary if we drop them from the construction of our shift-share index. Another possible concern would be if the shocks we identify are not truly unexpected and house prices have already priced them in. Given that the pre-trend is in the wrong direction, this is unlikely, but we can address this by including two lags of house price changes and divergence as controls. Similarly, it could be that controlling for two lags of industry divergence are not sufficient to capture the data generating process. Including six lags of industry divergence does not change the results. Further, one might be concerned that

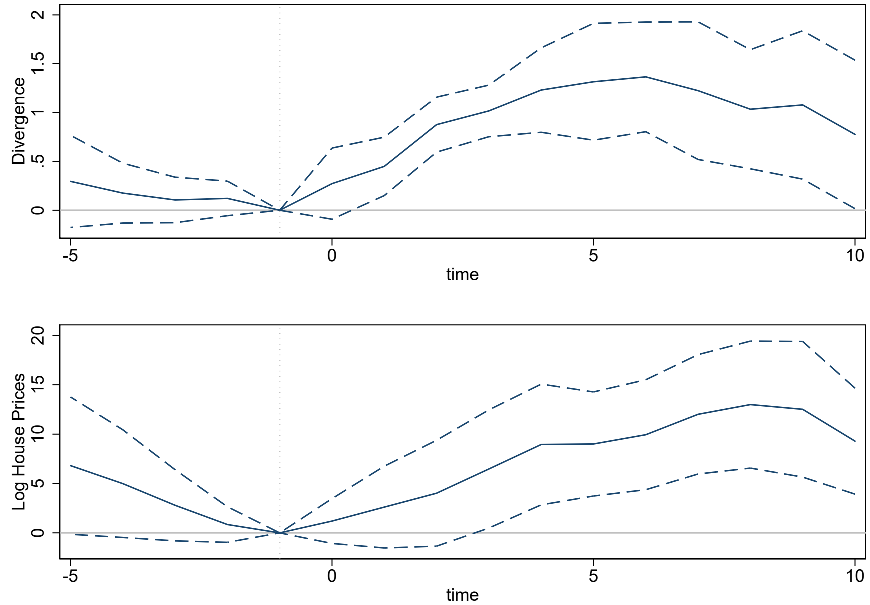


Figure 4: **Impulse Responses to Industry Divergence.** A local projection to innovations in the industry-driven divergence series, for regional divergence and house prices. Standard errors robust to heteroskedasticity and autocorrelation (bandwidth 3). Local projections estimated using Equation (2).

GDP growth is an important omitted variable, so we can add GDP growth in the concurrent year, as well as two lagged years, as controls. We can add the previous GDP growth controls and three years of ten-year interest rates changes, inflation, and income shares of the top 50 and top 1 percent as controls. None of these additional controls change the result.

Finally, in Appendix Figures A2 and A3 we show that we obtain similar results using one-year industry growth to construct the shift-share instrument. Innovations to ten-year divergence are very similar to one-year divergence, so one would expect the local projection to show similar results.

2 Theory

In this section, we propose a model to explain the relationship between divergence and house prices discussed in the previous section. Our model adds expectations and an asset pricing equation to a standard Rosen (1979)-Roback (1982) model.

Our model is purposefully simple. First, the simplicity makes our mechanism more clear and illustrates what assumptions are necessary to deliver the causal relationship we found in the previous section. In later sections, we show these assumptions are largely supported by the data. Second, due to its simplicity, the model makes clear predictions on non-targeted moments that distinguish it from other models. Being able to test these predictions adds plausibility to the causal relationship we found and the mechanisms that we propose to explain it.

2.1 Setup

Consider I regions, denoted by i. Time is discrete and indexed by t. There are mobile hand-to-mouth consumers and absentee landlords. Income in the model is region-specific and is an exogenous endowment.[28] Income growth is given by the following equation:

$$\log w_{it} - \log w_{i,t-1} = \lambda_t + \kappa_t \log w_{i,t-1} + \epsilon_{it} \tag{3}$$

where λ_t captures the national growth rate and κ_t represents regional divergence. Note that both are time-varying. ϵ_{it} is an idiosyncratic state-specific term.

Mobile hand-to-mouth consumers have Cobb-Douglas utility over a tradable good

[28] We make the assumption of exogenous wages and look at house prices as an endogenous outcome. This reflects our empirical exercise, where we found that plausibly exogenous changes to divergence had an effect on house prices.

and housing, and frictionlessly choose where to live. Their problem is given by:

$$U_t = \max_i \max_{c_{T,it}, c_{NT,it}, h_{it}} c_{T,it}^{1-\phi-\psi} c_{NT,it}^{\psi} h_{it}^{\phi}$$

subject to $c_{T,it} + p_{NT,it}c_{NT,it} + r_{it}h_{it} = w_{it}$, where $c_{T,it}$ is the consumption of tradable goods in region i at time t, $c_{NT,it}$ is the consumption of non-tradables, and h_{it} is housing. The price of tradables is normalized to 1.

Competitive firms produce tradable goods linearly with labor that has productivity w_{it}, hence the wage is pinned down at w_{it}. Competitive non-tradable firms produce goods $y_{NT,it} = L_{NT,it}^{1-\omega} H_{NT,it}^{\omega}$, hence the price of non-tradables is given by $p_{NT,it} = (1-\omega)^{\omega-1}\omega^{-\omega} w_{it}^{1-\omega} r_{it}^{\omega}$.

Free mobility leads to an indifference condition over their indirect utility a la Rosen (1979) and Roback (1982):

$$\log w_{it} - \alpha \log r_{it} = \log w_{jt} - \alpha \log r_{jt} \tag{4}$$

where $\alpha \equiv \frac{\phi+\omega\psi}{1-\psi(1-\omega)}$.

Absentee landlords are risk-neutral and rent the housing to the mobile consumers. We assume there are no bubbles, so house prices are given by the present discounted value of rents:

$$p_{i,t} = \sum_{s=t}^{\infty} \frac{1}{(1+R)^{s-t}} \mathbb{E}_t[r_{i,s}] \tag{5}$$

where R is the interest rate, for now assumed to be constant, and $r_{i,s}$ is the rent in location i at time s.

We assume that expectations of κ_t for the landlords are based on the regression from the previous section.[29] We further assume that landlords expect κ_t to remain

[29]As we show in Appendix Figure A4, many measures of regional income divergence look similar

at its current level forever. To put it another way, landlords are extrapolating recent trends in divergence into the infinite future. We defend this assumption in Section 3.

A housing supply curve in each region defines a relationship between housing construction and prices.

$$H_{it} = H_{i,t-1} + F_i(p_{it}) \tag{6}$$

where H is the total housing supply in a city and $F_i(\cdot)$ is strictly increasing. We allow F_i to vary by region, consistent with Saiz (2010). In the poorest region, house prices are determined by the cost of construction, which is exogenous to the model. This represents a perfectly elastic housing supply function in these areas, i.e. F is vertical.

$$p_{k_t,t} = \bar{p} \tag{7}$$

where $k_t = \text{argmin}_i w_{it}$.

Finally, per capita housing consumption—both direct consumption and indirect consumption through non-tradables—is given by the Cobb-Douglas utility, implying that

$$\frac{H_{it}}{L_{it}} = (\phi + \psi\omega)\frac{w_{it}}{r_{it}} \tag{8}$$

The equilibrium of this model is defined by equations (3)-(8). For a given rate of expected convergence κ_t and incomes w_{it}, the prices and rents are determined by the equations (3), (4), (5), and (7). These prices and rents imply a certain amount of housing and population by equations (6) and (8). Because the poorest region is perfectly elastic, they take the remaining population.

in the data.

2.2 Predictions

We can solve this model for rents and house prices in each region. Rents are given by:

$$\log r_{it} - \log \bar{r} = \frac{1}{\alpha} \log \frac{w_{it}}{\bar{w}_t} \tag{9}$$

where $\bar{w}_t$ is the income in the poorest region, and $\bar{r}$ is the rent in the poorest region, which is equal to $\frac{R}{1+R}\bar{p}$. Note that rents do not depend on divergence because they are determined solely by the current income premium over the lowest-income location. In other words, this expression uses only equations (4) and (7).

We can also solve the model for house prices:

$$\frac{p_{it}}{\bar{p}} = \frac{R}{1+R} \sum_{s=t}^{\infty} \frac{1}{(1+R)^{s-t}} \left(\frac{w_{it}}{\bar{w}_t}\right)^{(1+\kappa_t)^{s-t}/\alpha}$$

The right-hand side is the present discounted value of rent, divided by rent in the poorest area. These relative rents are governed by the relative wages, which grow at rate κ_t, i.e. divergence, each year.

A helpful log-linear approximation is that

$$\log p_{it} - \log \bar{p} \approx \frac{R}{R-\kappa_t} \frac{1}{\alpha} \log \frac{w_{it}}{\bar{w}_t} \tag{10}$$

This equation resembles the equation for rent, but with an extra term: $\frac{R}{R-\kappa_t}$.[30] When $\kappa_t = 0$, people expect wage differences across space to be the same forever, so prices and rents are proportional. When $\kappa_t > 0$ and people expect future income divergence, the difference in prices between richer and poorer regions is larger than the difference

[30] The log-linearization is around the case where $w_{it} = \bar{w}_t$ and $p_{it} = \bar{p}$ for the left-hand side. The log-approximation of the equation is $\log p_{it} - \log \bar{p} \approx \frac{R}{1+R} \sum_{s=t}^{\infty} \frac{1}{(1+R)^{s-t}} \frac{1}{\alpha} (1+\kappa_t)^{s-t} \log \frac{w_{it}}{\bar{w}_t}$ because near $w_{it} = \bar{w}$, the right-hand side sums to 1. Equation (10) is the series summation of that expression, which converges if $\kappa_t < R$.

in rents because people expect the rents to increase more in richer areas. Conversely if $\kappa_t < 0$, then the difference in prices is smaller than the difference in rents.[31]

The extra term resembles the formula for the Gordon growth model. Intuitively, the growth rate of rents depends on κ_t, so it is natural to have a similar equation. However, because the price of the house in the poorest region is pinned down by construction costs, the interest rate also appears in the numerator, unlike in the Gordon growth formula.

Equations (9) and (10) lead to the first four predictions:

Prediction 1: *Average rents are determined by the ratio of the average income over the income in the poorest region.*

Rents in any region are given by the difference between local income and income in the poorest region (Equation 9). The aggregate is simply the average over all the regions.

Prediction 2: *Average house prices are increasing in regional divergence.*

From Equation (10), when κ_t increases, prices rise everywhere but the poorest region (where the elastic housing supply assumption implies that they are equal to construction costs). So the average rises. Although other factors matter as well, divergence will be the primary driver of house prices in our calibration, matching what we see in the data. The ratio of the average wage to the lowest wage affects prices but to a lesser degree.

Prediction 3: *A cross-sectional regression of house prices on income has a higher estimated coefficient when divergence is large. In contrast, a cross-sectional regression of rents on income has a constant coefficient.*

Higher divergence increases the difference in house prices between high- and low-income areas. In a within-year regression of house prices on income, the model pre-

[31]The effects of interest rates on house prices are ambiguous. We discuss it further in Section 5.

dicts that the coefficient on income should be $\frac{1}{\alpha}\frac{R}{R-\kappa_t}$, so it is high when divergence is high (equation 10). For rents, the coefficient is $\frac{1}{\alpha}$, which is constant over time (equation 9).

Prediction 4: *Regional house prices are more sensitive to national house prices in higher income regions.*

Our model microfounds the reasons certain areas might have more "sensitive" house prices to national changes. In the poorest region, a change in κ_t has no effect on local house prices because they are close to construction.[32] But in the richest region, a change in κ_t has a large effect on house prices.[33]

Formally, by Equation (10), if the yearly change in state incomes are small compared to the effect of the change in divergence, then the national change in house prices is given by the change in $\frac{\partial p_t}{\partial \kappa_t} = \frac{R}{(R-\kappa_t)^2}\frac{1}{\alpha}(\log w_t - \log \bar{w}_t)$, where p_t is national house prices and w_t is average income in year t. The change in any state's individual house prices are given by $\frac{\partial p_{it}}{\partial \kappa_t} = \frac{R}{(R-\kappa_t)^2}\frac{1}{\alpha}(\log w_{i,t} - \log \bar{w}_t)$. So the sensitivity of the state's house prices should be given by $\frac{\log w_{it} - \log \bar{w}_t}{\log w_t - \log \bar{w}_t}$, which is linearly increasing in income.

Prediction 5: *In the two-region case, there should be more construction in the higher-income region when there is high regional divergence. In addition, population increases in the higher-income region.*

Intuitively, when house prices are high, they are highest in the highest-income cities, which produce more housing because they have upward-sloping supply curves.

[32] As we show in Appendix A.9, the poorer states are what drives divergence: high-income states have little correlation between divergence and their growth rates, whereas poor states have a very negative correlation. Therefore, this prediction emphasizes the GE nature of the model: the growth rate of the poor states affects house prices in the rich states, but not as much in the poor states themselves.

[33] This intuition only makes sense if the relative income of regions is relatively stable. In practice, states do change relative income, but the correlation of state income across time is high, even over many years.

So there should be more construction in the higher-income region. By the free mobility assumption, there should be migration into this region as well. But because cities can vary on both their income and housing supply elasticity, there is no general theorem on the direction of migration between any two particular cities. We can only make this prediction into a theorem in the two-region case. Recall that the poorer region's housing supply is perfectly elastic, and the higher-income region has a positive finite housing supply elasticity.[34]

2.3 Comparison to Other Models

Our five predictions help distinguish our model from others that might be able to match some subset of our data.

The fact that our model predicts different things for rents and house prices (e.g. Predictions 1, 2, and 3) immediately distinguishes it from theories that do not include either changes in expectations or a segmented market between owner-occupied and rental housing. Further, our story predicts changes in the price-rent ratio, even for the same house, consistent with the findings of Begley et al. (2019). Since changes to the price-rent ratio explain most of house price volatility, we view this as an important

[34] To show the prediction formally for the two-region case, consider a comparative static in which κ_t increases, $w_{rich,t}/w_{poor,t}$ increases, $w_{rich,t}$ weakly increases, and $w_{poor,t}$ weakly decreases. By the solution for house prices and equation (6), supply is given by:

$$H_{rich,t} = H_{rich,t-1} + F\left(\bar{p}\frac{R}{1+R}\sum_{s=t}^{\infty}\frac{1}{(1+R)^{s-t}}\left(\frac{w_{rich,t}}{w_{poor,t}}\right)^{(1+\kappa_t)^{s-t}/\alpha}\right)$$

which is increasing in both κ_t and $w_{rich,t}/w_{poor,t}$. Therefore the supply of housing in the rich city has increased.

By equation (9), rents in the rich region are given by $\log r_{rich,t} = \log r_{poor,t} + \frac{1}{\alpha}\log w_{rich,t} - \frac{1}{\alpha}\log w_{poor,t}$. Since $\frac{1}{\alpha} > 1$ and $w_{poor,t}$ is weakly decreasing, $\log r_{rich,t}$ is increasing by more than $\log w_{rich,t}$. By the Cobb-Douglas assumption, this corresponds to a decrease in per capita housing demand.

Because the supply of housing, $H_{rich,t}$, has gone up, and the per capita demand for housing, $w_{rich,t}/r_{rich,t}$, has decreased, then by equation (8), population must increase.

contribution. A model of segmented markets—a critical ingredient for the role of credit—would not make that prediction (Greenwald and Guren, 2021).

Our model also predicts substantial house price heterogeneity by regional income (Predictions 3 and 4). In principle, this distinguishes it from the class of models that explain regional heterogeneity through the interaction of a national housing demand shock (or expectations of a future housing demand shock) and different regional housing supply elasticities. However, due to the high correlation between housing supply elasticity and income (see Figure 6), there is no good way to empirically draw out this distinction.[35] However, these predictions rule out any theory that does not account for this heterogeneity.

The locations of construction and migration (Prediction 5) draw a more empirically-relevant distinction between our theory and theories based on a national housing demand shock. A national housing demand shock would drive people to move and build housing in lower-income housing-supply-elastic areas (Davidoff et al., 2016). A theory of regional divergence, however, predicts people move into high-income housing-supply-inelastic areas when house prices are highest.

Several of our predictions also draw a distinction between our theory and Ganong and Shoag (2017). In their theory, based on changing supply constraints, house prices and rents move together. Hence, Predictions 1, 2, and 3 can distinguish our theory from theirs. In addition, if supply constraints are causing higher house prices, we would expect people to move out of the rich high-housing-cost regions when house prices are high, meaning that Prediction 5 could also distinguish the stories.[36]

[35] If housing supply elasticities and income were uncorrelated, an econometrician could see which was better at explaining the cross-section of house price movements.

[36] The motivation for their paper is explaining the long-term rise in house prices and rents, not the fluctuations, which is supported by their finding of a steady increase in supply restrictions over time. Our predictions are not falsifying that claim. But they would in principle falsify the claim that their mechanism could explain short-run booms and busts in house prices.

Finally, our model provides a reason for expectations to change (Prediction 2). Many studies that have emphasized the role of expectations for house price fluctuations (Kaplan et al., 2019; Ben-David et al., 2019) do not focus on why expectations change.

3 Discussion of Model Assumptions

This section provides evidence for the assumptions of our model. Admittedly, the assumptions were chosen to be able to generate the relationship between regional divergence and house prices which we found in Section 1. Nonetheless, we wish to argue that they are reasonable when we look at the data. First, we show that it is important to include divergence in a model of state-level income growth and that it is reasonable for agents to base their expectations over divergence by measuring it over several years, such as the ten-year time frame we adopt. We also show that this resembles actual measures of expectations. Finally, we discuss our assumptions for regional differences in housing supply elasticity and the relationship between rent and income.

3.1 Including Divergence in the State Income Process

The growing interest by economists in regional divergence provides a reason that it ought to be included in models of state-level income growth (Ganong and Shoag, 2017; Berry and Glaeser, 2005; Moretti, 2013; Giannone, 2017). We go further in this section by providing statistical evidence that regional divergence matters.[37]

We show the R^2 from three regressions, where the outcome variable is the average

[37] We specify a state-level income process that is based on an exogenous divergence rate. The exogeneity is justified based on our empirical results where we show that changes in divergence are largely caused by relative industry growth rates, which we consider exogenous to the housing market.

Table 2: R^2 of regression of state-level income growth

	Estimating equation	R^2	Within R^2
No Divergence	$\frac{1}{10}\log(w_{it}/w_{i,t-10}) = \lambda_t + \epsilon_{it}$	0.77	0
Fixed Divergence	$\frac{1}{10}\log(w_{it}/w_{i,t-10}) = \lambda_t + \kappa \log w_{i,t-10} + \epsilon_{it}$	0.86	0.38
Time-varying Divergence	$\frac{1}{10}\log(w_{it}/w_{i,t-10}) = \lambda_t + \kappa_t \log w_{i,t-10} + \epsilon_{it}$	0.89	0.53

10-year state income growth. Each unit of observation is a state-year pair. The "Within R^2" column shows the percent of the variance explained after taking out the year fixed effects. The first regression, in Row (1) of Table 2, corresponds to the baseline, where state income growth is based on national income growth and an idiosyncratic factor. Under this specification, national income growth can explain 77 percent of the variation in state-level growth. The second regression, in Row (2), also includes the log of lagged income. This corresponds to including a fixed amount of convergence in every year. The model fit significantly improves, from 77 percent to 86 percent. Even better, a time-varying divergence, corresponding to the third regression and seen in Row (3), can explain significantly more, more than half of the cross-sectional variation within years.[38] This makes sense, as divergence has changed a lot over time, so allowing it to time-vary should improve the fit significantly.

What this analysis shows is that state-level income is not idiosyncratic. It depends on both national growth, but also significantly on regional divergence. By considering time-varying divergence, we can explain more than half of the state-level variance that a more naive model would consider "idiosyncratic."

Of course, just because regional divergence is helpful to explain the cross-section of state income growth does not make it a "fundamental" cause. Based on the literature and the instrument we used in Section 1, we think it is largely driven by different

[38] The adjusted within R^2 is 0.52, which is not that different. This is as expected since there are still well over 3000 degrees of freedom in this regression.

industries' growth rates (Barro and Sala-I-Martin, 1991; Giannone, 2017; Eckert et al., 2020). We wish to emphasize that in order to explain state income, a model ought to allow for some mechanism through which there is systematic and time-varying convergence or divergence.

Another way to show the importance of divergence is through factor analysis. In Appendix Section A.3, we use factor analysis to show not only that divergence is important, but also that it is more-or-less the second most important factor. Taking the two most important factors across the 49 state-level time series, we see in Figure A7 that the second factor is highly correlated to regional divergence and that the loadings on that factor are highly correlated to income.[39]

3.2 Sources of Expectations Over Divergence

The model assumes that expectations about future divergence are determined from recent divergence. We follow the literature (e.g., Barro and Sala-I-Martin, 1991) in measuring divergence using ten years of recent income data, but a natural question is whether this is a reasonable determinant of agents' expectations. There are two possible ways for this assumption to be true. One possibility is that our ten-year measure of divergence predicts future divergence one-for-one and our backwards looking expectations coincide with forward looking rational expectations. A second possibility is that agents expect more persistence in divergence than there truly is. Unfortunately, the persistence of the time series and how agents form expectations are two very difficult questions, neither of which we will fully solve. Instead, we provide evidence of two weaker things, which we nonetheless find informative. First, there is undoubtedly significant persistence in the time series of divergence. Second, people's expectations

[39]The first factor resembles national income growth, and most states have similar loadings near 1. The first factor explains 85.4 percent of the variance and the second factor explains 6.4 percent. No other factor explains more than 2.1 percent of the variance.

over local prices are consistent with the hypothesis that they form expectations over divergence in the way we propose.

The first important reason to think recent divergence is correlated with agents' expectations is that divergence is persistent in the data. Therefore, an agent with rational expectations would find the recent history of divergence salient.[40] In Appendix A.4 we show directly that past divergence has a quantitatively important impact on realized future incomes. When divergence was recently high, it would be correct to expect relatively more future growth in high-income states. Table A1 shows results of a state-level regression of wages on lagged divergence and control variables. Divergence shows a statistically significant and economically important relationship with future state income.

If divergence is persistent, why use ten years of data and not just the most recent year? In Appendix A.5, we look at the statistical properties of a one-year measure of divergence. An innovation in the time series of one-year divergence has a component that persists indefinitely. However, a larger component of that innovation is noise, and disappears within one or two years. Based on that, agents' expectations over divergence ought to be based on a "Goldilocks" length of time: short enough to be informative about the recent past, but long enough to not be mostly noise.

Of course, we could do more sophisticated things than our ten-year regression to measure divergence, and so we show in Section 4.3.1 that many sensible sources of expectations have similar predictions for house prices, including alternate numbers of years, measures based on other geographies, and agents that have approximately rational expectations based on a specific data-generating process for house prices. We choose to assume that expectations are based on the previous ten years because it

[40]Because of the high persistence, the recent history being salient would also hold with other modeling choices for expectations.

is the most common measure in the literature (e.g. Barro and Sala-I-Martin, 1991; Berry and Glaeser, 2005).

Another important reason to think that lagged divergence determines expectations comes from survey measures of expectations. The Michigan Survey of Consumers (MSC) asks respondents their expectations over the one-year change in prices, housing prices, and the respondent's income.[41] Ideally, we could directly measure every consumer's expectations of future incomes and prices in every state, and use that to calculate expected price and income divergence. In fact, we only know agents' personal expectations, along with what state they live in. Using this, we can run a yearly regression of expectations on state-level log income, and use the coefficients to measure implied divergence. More details about the construction of the expectations indexes are available in Appendix C.4.

Our preferred measure of expectations for this exercise is inflation expectations. The main reason we prefer this over income is that it is much less noisy, which makes sense because the survey's income questions ask respondents about expectations for their personal incomes, which are highly idiosyncratic. Importantly, inflation expectations—in the context of our model but also in general—should also reflect expectations for local income growth (Rosen, 1979; Roback, 1982; Moretti, 2013). Higher local income is passed through to local prices both because non-tradable prices become more expensive and also because rents increase in response to incomes (i.e. our Rosen (1979)-Roback (1982) assumption). Since rents and non-tradable goods are a large fraction of the consumer price index, this should be an important component

[41] Similar to the way the Michigan survey cleans price expectations, we censor particularly high and low income expectation responses, and we assign responses that indicate a direction but not a precise number to the mean of other responses in that year and state which share the same sign. We then average to a state-year data point using the survey weights. For all regressions using the Michigan Survey, we weight state data by the sum of the survey weights from the Michigan data (overall, there are more than 6000 respondents per year, but some states have less than ten).

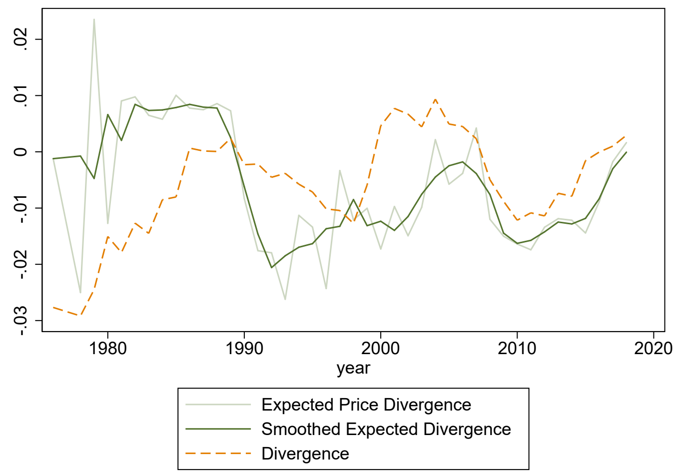


Figure 5: **Divergence in Expected Local Prices.** The Expected Divergence line is the coefficient of a regression of 1-year expected price on income growth from the Michigan Survey of Consumers on log income, weighted by survey weights. Smoothed Expected Divergence is a three-year moving average of the Expected Divergence line. Divergence is the line described in Figure 2.
Source: Michigan Survey of Consumers and calculations as described in the text.

of inflation expectations.

The relationship between expectations divergence and realized income divergence is shown in Figure 5. The two series fluctuate with similar timing, suggesting that the ten-year measure we use for divergence is approximately how people actually form expectations.

In Appendix A.6, we show similar results for house price divergence expectations and for personal income expectations. These series are also positively correlated to divergence, but noisier. As we mentioned above, the income measure is noisy because it asks about consumers' personal income expectations, when what we really want is expectations for local average incomes.

3.3 Housing Supply Elasticity

We make the assumption that the poorest region has a perfectly elastic housing supply due to the strong empirical relationship between housing supply elasticity, as measured by Saiz (2010), and income. We show this in Figure 6a. Higher income cities uniformly have low elasticities, but lower income cities often have very elastic housing supply, and one might hypothesize that areas outside of MSAs are probably even more elastic. In related work, Howard and Liebersohn (2021) consider a model of rents where there is a strong relation between elasticity and income growth. In this paper—because our focus is more on expectations—it is more tractable to make an extreme assumption of perfect elasticity in the lowest-income state.

We should note that there exists a growing literature on why housing supply elasticities might endogenously be correlated to high income and high house price areas (e.g. Parkhomenko, 2018; Bunten, 2017). We take the relationship for granted in our model.

3.4 Income-Rent Relationship

Equation (4) implies a perfectly linear relationship between rents and incomes in the cross-section of states. This is supported by the fact that the data show a high cross-state correlation between per capita income and rent per square foot (0.89 in 2015). It is also a fairly stable relationship, which we discuss as a prediction of our model.[42] In addition, our other work, Howard and Liebersohn (2021), argues that people's location demand is quite elastic in the long run and since a significant part of the value of a house will be based on rents far in the future, that is the quantitatively

[42] Our model abstracts from amenities. To the extent they are unrelated to income, they will serve as a residual to our model which would average out over many states. To the extent that they are correlated, we could incorporate them in our calibration of α.

important measure.[43]

Because of this assumption, the exact housing supply elasticities of states besides the perfectly-elastic one do not matter for prices. Of course, they would play a critical role for quantities. Alternatively, if we relaxed the assumption of perfect mobility, housing supply elasticities would play a role in determining prices (Howard and Liebersohn, 2021) but because of the strong relationship in Figure 6b, we feel that perfect mobility is a reasonable benchmark and it makes the model significantly more tractable.

Besides free mobility, equation (4) also requires the Cobb-Douglas assumption for utility. While there is evidence against unit elasticities of housing consumption to rents or income (Albouy, Ehrlich and Liu, 2016; Polinsky and Ellwood, 1979; Hanushek and Quigley, 1980; Mayo, 1981), any utility function, combined with free mobility, will generate an indifference condition similar to equation (4).

4 Predictions

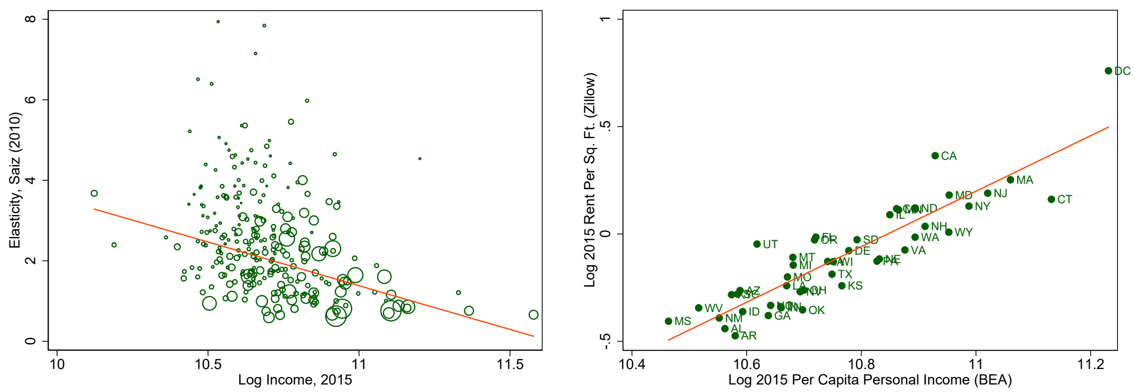
In this section, we check the five predictions of the model, qualitatively and quantitatively.

4.1 Calibration

Predictions 1-4 are qualitative, i.e. they suggest a correlation in the time-series or cross-section. They are also quantitative; for a set of model parameters, the relationships should have specific magnitudes.[44] To check the quantitative aspects, we

[43]There are a huge range of calibrations for long-run population mobility that are used in the literature, ranging from a population elasticity to wages of about 3 to about infinity.

[44]Prediction 5 depends on the precise magnitude of supply elasticities, which have likely changed over time, so it is hard to make any quantitative prediction.



(a) Housing Supply Elasticity and Income

(b) Rosen (1979)-Roback (1982)

Figure 6: **Checking Assumptions in the Data.** In (a), each dot represents an MSA, for which Saiz (2010) computed housing supply elasticities. The x-value of the point corresponds to the 2015 per capita personal income (BEA) in the counties making up that MSA. The size of the dot is proportional to the population, and the line of best fit is also population-weighted. In (b), each point is a state, and it relates the 2015 rent per square foot from Zillow to the 2015 per capita personal income.

parametrize the model, though it should be noted that one could not believe the parametrization and still be interested in the qualitative predictions.

There are only a handful of parameters to calibrate for this model. We calibrate $\alpha = 0.62$ following Moretti (2013), which accounts for the fact that rental prices are passed on into other goods. We calibrate $R = 0.05$.

The trickiest part of the model to calibrate is the wage of the lowest-income region. One option would be to use the lowest-income state, but that suffers from a few drawbacks. First, it can be quite noisy. To address this, we take the average of the five lowest-income states. Second, even the lowest-income states have experienced urbanization over the last ninety years. To account for this, we include a trend term, which we set to half a percent per year.[45] So our measure of $\bar{w}_t$ is given by the average income of the five lowest-income states in year t, discounted by half a percent for each

[45]This is motivated by the fact that the fifth percentile of state's income has grown half a percent faster than the fifth percentile of CBSA income since 1969, the first year for which we can measure CBSA income.

year since 1929.[46]

4.2 The Time Series of Rents

The first prediction of the model was that regional income inequality (specifically, the average difference relative to the poorest region) pinned down the average rent level in the country. When regional incomes are more unequal, the average rent should be higher because it represents a premium over states that are much lower-income.

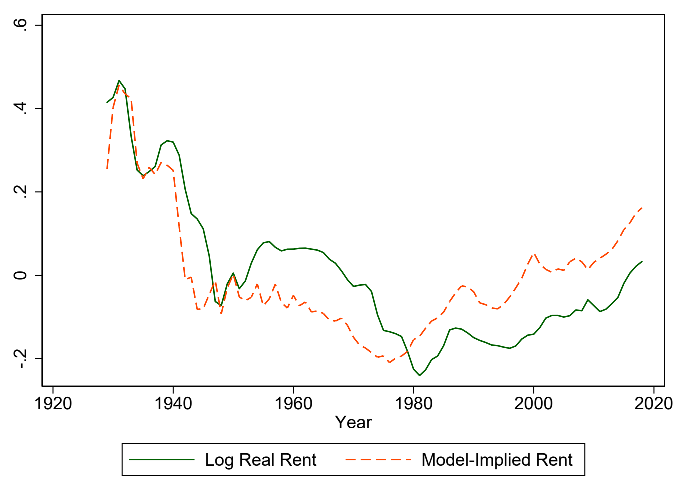


Figure 7: **Average rents, model-implied and data.** Data comes from the BLS's CPI rent series and is deflated by overall CPI.

In Figure 7, we show that the model-implied rents, which are based only on income data and the previous calibration, do a good job of explaining aggregate rents. The large decline in the pre-war era, the gradual decline post-war, and the rise since 1980 are all present in the model, and many of the fluctuations are as well. The magnitudes are in line with the data.[47]

[46]The primary effect of this calibration is to introduce an upward trend in both rents and house prices, which is going to help us match the data. An alternative way to match the trend would be to assume that construction costs have increased over time, but given the fact that urbanization has occurred everywhere and that there is little evidence of increasing construction costs, we prefer to make this assumption.

[47]If we instead wished to match the time series given by Crone et al. (2010), we would need to

We believe we are the first paper to document the relationship between regional income inequality and the level of average rents over such a long time period. In Appendix A.2, we show that this is not because of the specific measure of regional income inequality that we are using. In fact, the standard deviation and other dispersion measures show a very similar overall pattern to rents.

4.3 The Time Series of House Prices

The second prediction of the model was that divergence should be related to aggregate house prices. This was shown as motivation in Figure 2, confirming this relationship qualitatively. Table 1 showed that the relationship was similar and statistically significant. Many other measures of divergence are shown in Appendix Figure A4, including estimates using other lag lengths and weighting schemes. Appendix Figure A5 shows that the results are similar when using CBSAs instead of states. In this section, we check that the magnitudes of the model are correct as well.

Figure 8 shows the model-implied house price series, next to the data. The aggregate is a population-weighted average of the state-level model-implied house prices, using the calibration from the previous section. Since World War II, the model and data line up fairly well. The correlation between model implied house prices and the real house price index is 0.47 (statistically significant at 1 percent). We use a Hodrick-Prescott (HP) to separate real and model-implied house prices into trend and cyclical components.[48] Both the cyclical and trend components of model-implied house prices are correlated to the components of house prices. The correlation between the trend components is 0.65 and the correlation between cyclical components

assume that the growth rate of income in the poorest five states versus the $\bar{w}_t$ in the model were about 1 percent higher per year. Changing this calibration has a comparatively small visual effect on the time series of house prices because the fluctuations are larger, and our model actually mildly underpredicts the trend.

[48]We use a smoothing parameter of 6.25, as suggested by Ravn and Uhlig (2002).

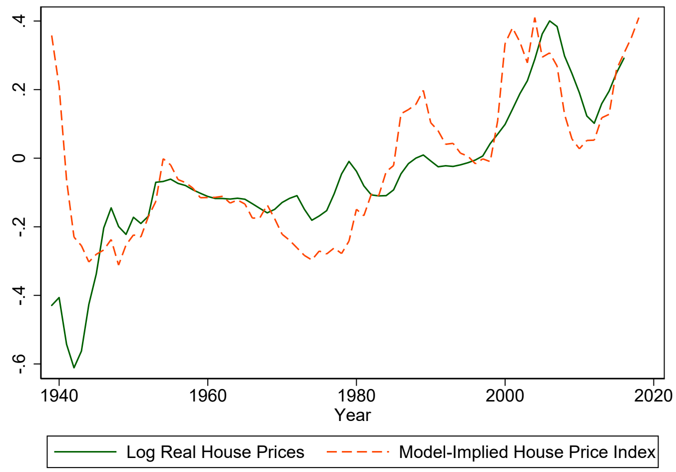


Figure 8: **Average house prices, model-implied and data.** House price series from Knoll et al. (2017) and deflated by CPI.

is 0.39, both statistically significant at 1 percent. Matching the time series of rents and house prices has been a challenge for the literature, and we believe ours is the first paper to even try to match such a long time series. Furthermore, we do so without assuming that housing and rental markets are segmented.

The model does miss the time series of house prices in two places. First, it predicts a big decline in the early 1940s compared to what actually happened. Given that the ten years prior to 1939 involved the Great Depression and the prospect of World War II, we think it is probable that the ten-year divergence rate is unrepresentative of future divergence expectations, and that is where the model breaks down.[49]

Another place where the model misses is that it does not predict a small boom in the late 1970s, and it predicts too large of a boom in the late 1980s. In Appendix B, we show that a model with changing interest rates and construction costs can better match house prices during this time period. Importantly, construction costs rose in

[49]The data at this time comes from newspaper advertisements in Chicago, Los Angeles, New Orleans, New York, and Washington D.C. Another possibility is that this data is not an accurate depiction of the national housing market. The data is more geographically representative and is based on constant-quality from 1953 onward. See Knoll et al. (2017) for details.

the 1970s and fell in the 1980s, helping to explain the timing.[50] Interest rates are also helpful because they dampen the effect of changes to regional divergence. We discuss the role of interest rates further in Section 5. Even with the additional features, the time series of house prices is primarily driven by regional divergence.

4.3.1 Robustness of House Price Results to Alternative Assumptions Regarding Expectations

In Figure 9(a), we investigate the robustness of our house price result, specifically with regards to our expectations assumption. To do that, we present other reasonable assumptions about how agents predict future divergence, and show that they still generate realistic house price movements.

The first alternative way would be to measure divergence using cities instead of states, but otherwise form expectations in an identical manner. Unfortunately, we can only construct this measure since 1979 due to data availability, but the fit is better, as the relative size of the 1990s boom and the 2000s boom are closer to the data, and the timing of the 2000s boom is slightly improved.

Other alternative sources of expectations involve using 8 or 12 years instead of 10 years of recent data. Using 12 years improves the timing a bit, while 8 years is a little worse.

The final alternative we present is an assumption that would be close to "rational expectations," if divergence follows a certain process. Specifically, we assume that divergence is generated by

$$\text{Divergence}_t = \chi_t + \epsilon_t \tag{11}$$

where χ_t is a unit root process, where the first-difference has variance σ^2_χ and ϵ_t is an

[50] Recall that construction costs were significant in explaining the time series of house prices in Table 1.

AR(1) process with persistence ρ and variance σ_ϵ^2.

We assume agents measure divergence in every period by estimating

$$\Delta \log w_{it} = \kappa_t \log w_{it-1} + \alpha_t + \epsilon_{it} \tag{12}$$

which is a 1-year measure of divergence. We then estimate χ_t, ϵ_t, σ_χ^2, ρ, and σ_ϵ^2 using a Kalman filter on $\hat{\kappa}_t$. Finally, we assume that divergence expectations at time t for time $t+s$ are given by

$$\mathbb{E}_t[\kappa_{t+s}] = \hat{\chi}_t + \rho^s \hat{\epsilon}_t \tag{13}$$

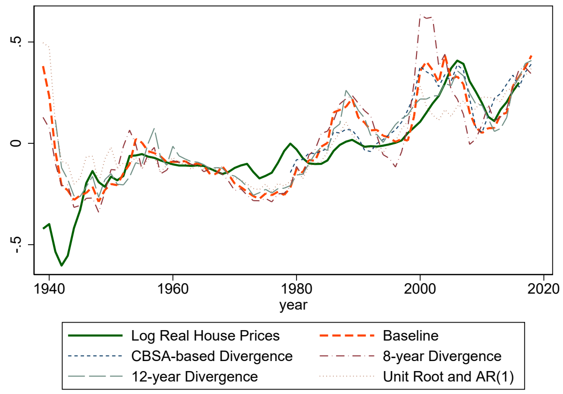
This is the true expectation of future divergence if the true model is the model given by (11). We then simulate the expectations of future rents based on the divergence in (13), and use that to calculate house prices in the current period.[51] We think this is a reasonable model of how divergence evolves, and if agents believe that model and form expectations based on expected divergence as described above, then it would generate results akin to assuming divergence is based on the previous 10 years.[52]

However, it is not the case that any assumption would work, which we show in Figure 9(b) and (c). In Panel (b), we present assumptions that generate too little volatility in house prices. The perfect foresight model assumes that agents know the

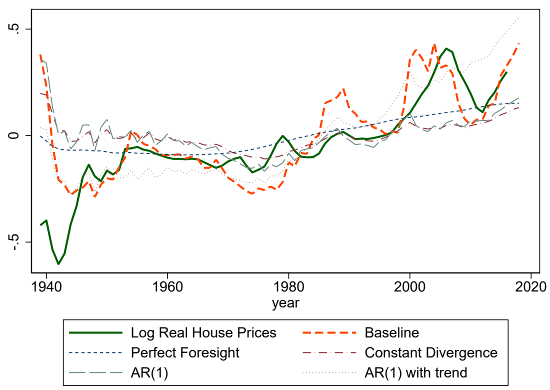
[51] The equation for house prices, when expectations of divergence are not constant is given by:

$$\frac{p_{it}}{\bar{p}} = \frac{R}{1+R} \sum_{s=t}^{\infty} \frac{1}{(1+R)^{s-t}} \mathbb{E}_t \left[\left(\frac{w_{it}}{\bar{w}_t} \right)^{\frac{\Pi_{j=0}^{s-t}(1+\kappa_{t+j})}{\alpha}} \right]$$

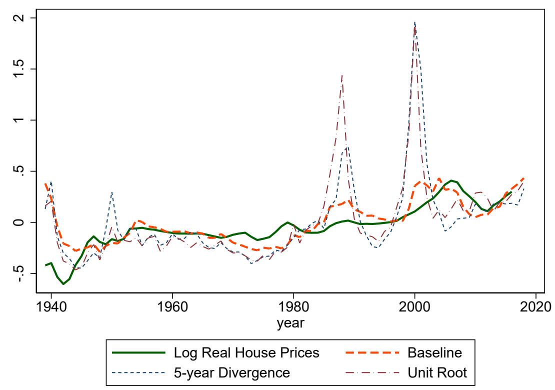
[52] There is a small difference between these expectations and truly "rational expectations," in that these agents do not take into account the uncertainty in how divergence will evolve going forward. We model it this way because if the unit root part of divergence drifts to be above R with positive probability, house prices become unbounded under rational expectations. In the Kalman filter, χ_t is always far from R, so the possibility is remote. Adding a feature where χ_t is bounded by some number less than R could be combined with truly rational expectations to deliver a similar house price path.



(a) Similar results to 10-year divergence



(b) Not enough volatility in house prices



(c) Too much volatility in house prices

Figure 9: Alternative Assumptions on Divergence Expectations.

true future path of income (we assume relative incomes remain the same after 2018 because we had to assume something). This generates almost no volatility in house prices. Similarly, if agents assume that, going forward, divergence will be the average amount of divergence, that does not generate much volatility. If agents assume that the process generating divergence is a simple AR(1) and use the expected divergence from that model to price housing, that does not generate enough volatility in house prices. Even adding an increasing trend term to the AR(1) does not generate enough volatility, although it can do a better job matching the increase in house prices over time.[53]

In Panel (c), we present assumptions that generate too much volatility in house prices. If agents assume the true model of divergence is from (11), but that the ϵ_t is i.i.d. instead of an AR(1), the house prices will have too much volatility. Similarly, if agents used five years to generate divergence expectations, the implied house prices would be too volatile. In particular, there are large spikes in the models' house prices when divergence expectations get too close to R,[54] and, in fact, if you shorten the range to less than five, there are periods in which house prices diverge to infinity.

We think this exercise highlights the key parts of our expectations assumption. On the one hand, it demonstrates that there is nothing magical about our specific assumptions. There is even a version of expectations that is close to rational and which could generate similar results. But it also shows what is essential. Matching house prices does require that the expectations over divergence are changing quickly: assumptions in which long-term divergence are anchored do not generate enough volatility. It also requires that the divergence results do not change too quickly based on noise in very recent divergence. Using only the recent five years or beliefs that divergence comes from a process with only a little bit of noise, generate way too much volatility in house prices.

4.4 The Cross-Section of House Prices

Prediction 3 of the model is that the regression coefficient of a cross-sectional regression of house prices on income should be large when divergence is high. In fact, the model predicts that this coefficient should be $\frac{1}{\alpha}\frac{R}{R-\kappa_t}$. Using the previous calibration,

[53] We have to assume divergence goes to zero after 2050 in order for house prices to remain bounded.

[54] When divergence and interest rates are close together, the denominator of equation (10) gets close to zero, making house prices grow without bound.

we can compare the coefficient β_t from the regression

$$\log p_{it} = \beta_t \log w_{it} + \gamma_t + \epsilon_{it}$$

to the predicted quantity from the model. Note that this regression estimates a different β_t for each year.

To run this regression, we use a combination of Zillow data and the FHFA house price index to measure house prices per square foot over time.[55] See Section C.3 for more details.

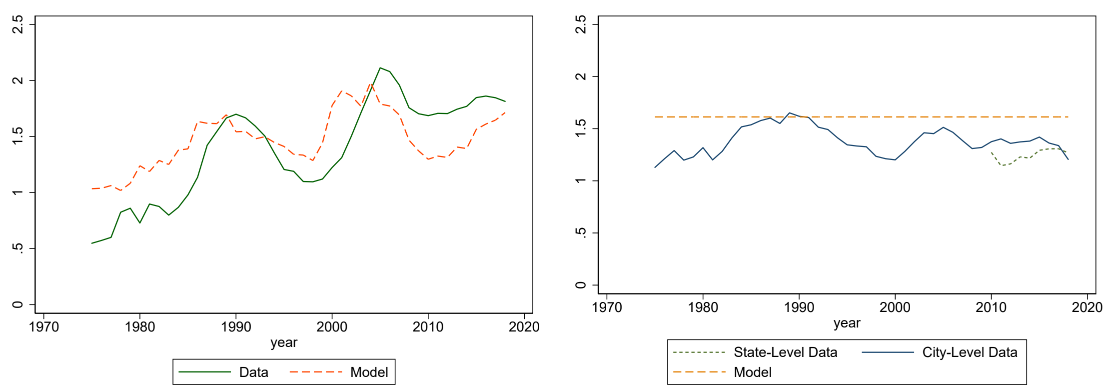


Figure 10: **Cross-sectional relationship between house prices and income, and rents and income.** A regression of house prices (left) and rents (right) on income across states, by year, in the model and the data.

The estimated β_t's and the quantity from the model are shown in Figure 10. Both the data and the model feature a large increase during the 2000s boom and a smaller increase in the late 1980s.

In contrast to house prices, the model predicts that rents and income should have a constant relationship, $\frac{1}{\alpha}$. We can estimate the same regression with rents as the dependent variable. To do this, we use Zillow data on rents spliced with rental price

[55]The ideal measure would not adjust for features of the location, such as nearby jobs, but would adjust for features of the housing stock, such as the age of the building.

indices. We are not aware of any constant-quality rental price indices for states, so we use the city as our unit of analysis and use the BLS index, which is available for 21 cities. As we expected, this cross-sectional regression coefficient is much flatter over time (right side of Figure 10). We also plot the regression using state as our level of analysis. The magnitude is roughly similar in recent years, but we cannot extend this before the start of Zillow data in 2010.

4.5 The Sensitivity of State House Prices

Prediction 4 of the model was that higher-income states would have higher sensitivities to national house prices. To measure sensitivity, we estimate the regression of the one-year change in local house prices on the one-year change in national house prices, state-by-state.

$$\Delta p_{it} = \beta_i \Delta p_t + \epsilon_{it}$$

where Δp_t is the national house price change, and β_i is state-specific. We also run the same regression on the predicted house prices from the model.[56]

The results are in Figure 11. In green are the β_i's from the regression on the data, and the orange crosses come from the same regression, but using the model-predicted house prices. The key result is that both are increasing in income and have similar magnitudes. The poor states are only slightly sensitive to national divergence, whereas the rich states are much more sensitive.[57] Our model fails to explain the high sensitivities of Nevada, California, Florida, and Arizona, which all had particularly

[56] Recall that sensitivity would be determined by income, only if most of the change in house prices was due to changes in κ_t rather than relative incomes. Because the relative incomes change as well, we expect a positive relationship between sensitivity and income, but not a one-to-one correlation. Running the same regression on the model-generated house prices gives us a sense of the variation that would naturally come from the changes in relative incomes.

[57] Appendix A.9 shows that income does not have the same pattern: poor states' income growths are negatively strongly correlated to divergence, whereas rich states' are not that correlated. So this pattern is not simply because incomes in high-states are more sensitive.

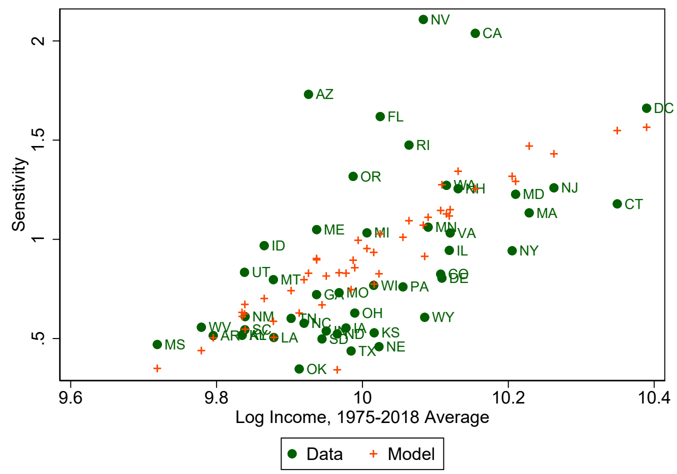


Figure 11: The sensitivity of state house prices to national divergence, model and data

large booms in the early 2000s.

In addition to this measure of sensitivity, other measures have been used in the literature. We show that some prominent examples of these are also highly related to income in Appendix A.8.

4.5.1 State-Level Model

Potentially, the model could also be used to understand house prices and population movements within individual states, instead of estimating it across the entire United States. We could imagine using the same calibration and feeding in county-level incomes from within a single state, rather than state-level incomes from across the country. We could then compare the model performance state-by-state. In fact, there are a few reasons to think that the model might perform well in this smaller setting: first, most moves do not cross state boundaries so the free mobility assumption is even more plausible within states; second, the model will fit well if supply in poor counties is more elastic than in poor states.[58] On the other hand, it is less clear whether people's expectations are more related to national income divergence or within-state income divergence. If people in the states predict future divergence based more on national divergence than within-state divergence then the state model might be inappropriate.

To explore this, we estimate the model using a panel of county incomes since 1969. The estimates are calculated in exactly the same way as our main results, except treating counties as "states." This means that we assume that the poorest five counties in each state have infinite housing supply elasticity and we measure divergence across counties within the state.

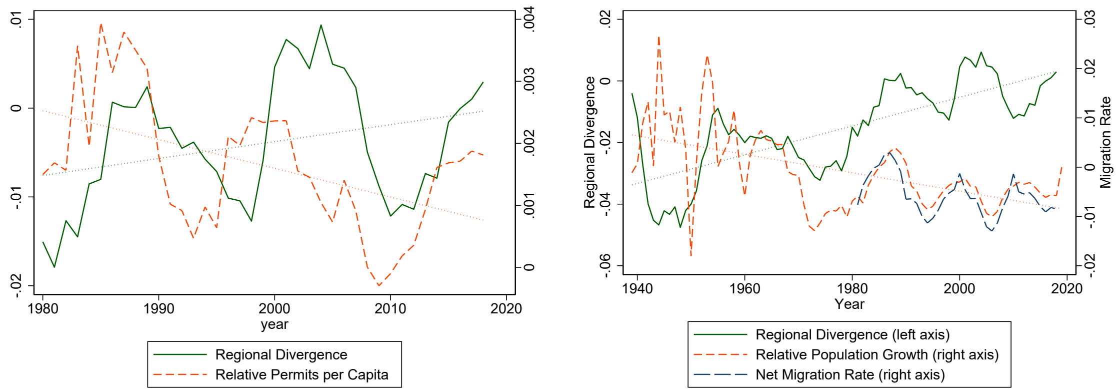
Figure A11 in Appendix A.7 shows model-implied house prices and actual real house prices for the six largest states. Model-implied house prices and actual house prices track closely for all states except Texas. Texas fits the data much better when we population-weight the divergence equation, suggesting that the estimated fluctuations in divergence are driven by incomes in low-income, low-population counties. The bivariate regression estimate using data from all states yields a coefficient of $\beta = 0.70$.[59] One reason the model might do well is that the within-state estimates are not that different than national estimates of divergence, for several of the states.

4.6 Construction and Migration

Our model finally predicts that when divergence is high, high-income states should have more construction. Higher prices are due to greater demand in high-income regions, which leads to more construction there. For the same reason, we should see relative population movements into the higher-income region. These predictions

[58] This second reason is, of course, debatable, especially for expensive and highly-regulated states like California.

[59] The regression of model-predicted prices on actual prices, while controlling for a state-specific time trend, has a coefficient of 0.7 and a t-statistic of 6.87.



(a) Permits Per Capita (b) Migration

Figure 12: **Regional Divergence, Relative Permits Per Capita, and Net Migration in Higher Income States.** States are divided by income in 1970. In (a), the orange line is the difference between annual construction permits per capita each year between the high-income group and the low-income group. In (b), we show the relative migration rate and population growth, which we can do over a longer time period. Linear trends are shown in dotted lines in each panel.

help distinguish between housing supply stories, in which people are pushed out of high-income areas by high house prices, and our story, in which people are drawn to high-income areas by the rising incomes.[60]

To test this, we divide the country into high-income states and low-income states in 1970, and compare the permits as a percent of population in the two groups over time.[61] This is seen in Figure 12(a). The high-income states had more permits

[60]This prediction is related to findings by Davidoff et al. (2016), who shows that during the early 2000s housing boom, there was less relative construction in higher-income regions than in low income regions. Our model is consistent with the findings in (Davidoff et al., 2016). This test of our model extends those results to previous time periods.

[61]The reader may wonder why we do not regress migration on income levels as a test of the prediction. We think there are two downsides to this. The first downside is that we know that housing supply elasticities and income are correlated. So divergence being high is not a robust prediction of higher population growth in high-income areas. In the two-region case, it is a prediction of the model, but with more regions, the fact that high-income regions are also less-housing-elastic may dominate. In fact, during recent years when divergence is high, the largest population growth has been in middle-income cities, where migrants can receive the gains of higher wages but where it is still possible to add additional housing (Howard and Liebersohn, 2021).

The second issue is that it is well-documented that building housing has gotten harder over time, especially in high-income cities Ganong and Shoag (2017). Given that divergence has risen during this time, this could lead to a spurious negative finding, where at times of highest divergence, there relative to trend in times where regional divergence is high relative to trend, and fewer in times when regional divergence is low relative to trend.

In Figure 12(b), we create a similar figure, but with migration instead of permits. The results in this figure are similar as for construction, but noisier. Before the 1980s, we are limited by the data to studying relative population growth rates. In recent years, we are able to verify that the difference is due to migration, comparing only migration rates between the two regions. Specifically, the richer states' relative growth is increasing during the housing booms in the 1950s, the late 1980s, the 2000s, and during the recent housing price increase. As with Figure 8, we neither expect nor find a strong relationship between divergence and house prices in the years during and shortly after World War II.

Looking at Figure 12(b), divergence is on an upward trend, while the relative movement of people into high income states is on a downward trend. This is likely due to the fact that housing has become harder to build, especially in rich high-density locations (Ganong and Shoag, 2017). We think our theory is doing a good job of matching some of the fluctuations in the line, which would not be accounted for by this gradual change in housing supply conditions. In Appendix A.10, we show that if we discipline the model's housing supply functions, we can even better match the patterns in Figure 12(b).

5 Role of Interest Rates

The model makes new predictions for the effect of interest rates on the housing market.[62] The direct effect of an interest rate change on prices is small, and the sign is

is the least population growth in those cities.

[62]The role of interest rates is somewhat controversial. Dokko, Doyle, Kiley, Kim, Sherlund, Sim and Van Den Heuvel (2011), Campbell, Davis, Gallin and Martin (2009), and Glaeser et al. (2012)

actually ambiguous: it depends on whether income is converging or diverging. However, interest rates play a large indirect role. For empirically reasonable values, lower interest rates make house prices more sensitive to divergence. Hence, when rates are low, house prices change more in response to a change in divergence.

To see both of these facts, we consider the partial derivative of house prices with respect to interest rates, and then the cross-partial derivative of house prices with respect to interest rates and divergence.

$$\begin{aligned}
\frac{\partial \log p_{it}}{\partial R} &= \frac{1}{\alpha}\frac{-\kappa_t}{(R-\kappa_t)^2}(\log w_{it} - \log \bar{w}_t) \\
\frac{\partial^2 \log p_{it}}{\partial R \partial \kappa_t} &= \frac{1}{\alpha}\frac{-R-\kappa_t}{(R-\kappa_t)^3}(\log w_{it} - \log \bar{w}_t)
\end{aligned}$$

In recent years, κ_t has been close to zero. Hence the top equation implies that interest rate changes have only had a small direct effect on house prices. This effect was sometimes positive and sometimes negative, depending on the sign of κ_t.

However, for empirically plausible values of κ_t and R (where $R > |\kappa_t|$), the cross-partial shows that lower interest rates make prices more sensitive to κ_t. In recent years, when interest rates have been low, we would expect house prices to have larger swings than if interest rates had been higher. For example, if the relevant interest rate declined from 6 percent to 4 percent, at a time when κ_t was approximately zero, then the house price sensitivity to divergence would increase by 50 percent. This means that the housing boom and bust of the 2000s would both have been substantially smaller if interest rates had been higher.[63]

---

argue interest rates cannot explain big swings in house prices, while Taylor (2007) notably argues that monetary policy was largely responsible for the housing boom. Jordà et al. (2015) finds positive effects across countries.

[63]The magnitudes should be taken with a grain of salt, given their sensitivity to small changes in the interest rate or the measurement of divergence. Nonetheless, this sensitivity is precisely why small changes in interest rates can have such a big impact on house price sensitivity to divergence. It is a robust fact that interest rates have been trending downward since the 1980s (e.g. Mian, Straub

The intuition behind the second result is that when interest rates are low, the present value of rents are weighted more heavily toward the future. Divergence has a larger effect on wages and rents in the future, so low interest rates make divergence more important.

In Appendix B, we present a model augmented by changing interest rates, and consistent with our prediction in this section, dynamic rates do help us better match the data. The high interest rates in the 1980s make house prices a bit less sensitive to regional divergence, and so our model does not overestimate the boom during that time as much. However, consistent with our point that there is no direct effect, adding dynamic interest rates do not have a large effect on the time series of house prices beyond that marginal improvement.

6 Conclusion

The contribution of this paper is to provide a parsimonious model of the time series and cross-section of house prices and rents in the United States for the past ninety years. Because housing is elastically supplied in low-income areas, greater regional income inequality causes higher average rents. House prices are the present value of expected rents, so higher expected regional inequality causes current house prices to be higher. This model unifies data on rents, house prices, migration, and expectations. Given the results of the model, we also show that there are important policy implications in that low interest rates can increase the volatility of house prices.

One of the successes of the model is its ability to explain the recent trends in house prices and rents, including the boom and bust of the 2000's. Throughout the paper, we have discussed this experience tangentially, but it also serves as a good recap of

and Sufi, 2021), which we think can help explain the high volatility of house prices in recent years. The exact magnitudes are harder to pin down.

many of our main points. In our view, the cause of the initial boom was an increase in regional divergence, led primarily by a growth in the professional services industry, an industry concentrated in high-income regions. People expected this growth to continue, leading them to also expect high future rents in the high-income cities. This raised house prices significantly, especially in high-income regions. When the growth rate of services slowed down, there was a corresponding bust in house prices. All of this was exacerbated by the fact that interest rates were low, making house prices more sensitive to changes in divergence.

Our model misses in a couple of places. We think the augmented model in Appendix B with time-varying interest rates and construction costs is sufficient in order to understand the 1970s boom and why our model overestimates the 1980s boom. However, our biggest miss is house prices at the start of our sample, and we think this is fertile grounds for further research. Given that our model does not have trouble with rents, we think it most likely that the Great Depression or World War II severed the link between recent divergence and divergence expectations.

References

Acemoglu, Daron and Pascual Restrepo, "Robots and jobs: Evidence from US labor markets," *Journal of Political Economy*, 2020, *128* (6), 2188–2244.

Adam, Klaus, Pei Kuang, and Albert Marcet, "House price booms and the current account," *NBER Macroeconomics Annual*, 2012, *26* (1), 77–122.

Adelino, Manuel, Antoinette Schoar, and Felipe Severino, "Credit supply and House Prices: Evidence From Mortgage Market Segmentation," 2013. NBER Working Paper 17832.

Albouy, David, Gabriel Ehrlich, and Yingyi Liu, "Housing demand, cost-of-living inequality, and the affordability crisis," Technical Report 2016. NBER Working Paper 22816.

Alvaredo, Facundo, Lucas Chancel, Thomas Piketty, Emmanuel Saez, and Gabriel Zucman, "Global Inequality Dynamics: New Findings from WID.world," *American Economic Review*, May 2017, *107* (5), 404–09.

Ambrose, Brent W and Thomas G Thibodeau, "Have the GSE affordable housing goals increased the supply of mortgage credit?," *Regional Science and Urban Economics*, 2004, *34* (3), 263–273.

Armona, Luis, Andreas Fuster, and Basit Zafar, "Home price expectations and behaviour: Evidence from a randomized information experiment," *The Review of Economic Studies*, 2019, *86* (4), 1371–1410.

Barro, Robert J. and Xavier Sala-I-Martin, "Convergence Across States and Regions," *Brookings Papers on Economic Activity*, 1991, *1991* (1), 107–182.

Bartik, Timothy J, "Who benefits from state and local economic development policies?," 1991.

_ **and Nathan Sotherland**, "Local Job Multipliers in the United States: Variation with Local Characteristics and with High-Tech Shocks," 2019.

Begley, Jaclene, Lara Loewenstein, and Paul S. Willen, "The Rent-Price Ratio During the Boom and Bust: Measurement and Implications," 2019.

Ben-David, Itzhak, Pascal Towbin, and Sebastian Weber, "Expectations During the US Housing Boom: Inferring Beliefs from Actions," 2019. NBER Working Paper 25702.

Berry, Christopher R and Edward L Glaeser, "The divergence of human capital levels across cities," *Papers in Regional Science*, 2005, *84* (3), 407–444.

Borusyak, Kirill, Peter Hull, and Xavier Jaravel, "Quasi-experimental shift-share research designs," *The Review of Economic Studies*, 2022, *89* (1), 181–213.

Bunten, Devin, "Is the rent too high? Aggregate implications of local land-use regulation," 2017.

Burnside, Craig, Martin Eichenbaum, and Sergio Rebelo, "Understanding booms and busts in housing markets," *Journal of Political Economy*, 2016, *124* (4), 1088–1147.

Campbell, Sean D, Morris A Davis, Joshua Gallin, and Robert F Martin, "What moves housing markets: A variance decomposition of the rent–price ratio," *Journal of Urban Economics*, 2009, *66* (2), 90–102.

Chodorow-Reich, Gabriel, Adam M Guren, and Timothy J McQuade, "The 2000s Housing Cycle With 2020 Hindsight: A Neo-Kindlebergerian View," 2021. NBER Working Paper 29140.

Crone, Theodore M, Leonard I Nakamura, and Richard Voith, "Rents have been rising, not falling, in the postwar period," *The Review of Economics and Statistics*, 2010, *92* (3), 628–642.

Davidoff, Thomas et al., "Supply Constraints Are Not Valid Instrumental Variables for Home Prices Because They Are Correlated With Many Demand Factors," *Critical Finance Review*, 2016, *5* (2), 177–206.

DeFusco, Anthony A, Charles G Nathanson, and Eric Zwick, "Speculative dynamics of prices and volume," *Journal of Financial Economics*, 2022, *146* (1), 205–229.

Dokko, Jane, Brian M Doyle, Michael T Kiley, Jinill Kim, Shane Sherlund, Jae Sim, and Skander Van Den Heuvel, "Monetary policy and the global housing bubble," *Economic Policy*, 2011, *26* (66), 237–287.

Eckert, Fabian, Sharat Ganapati, and Conor Walsh, "Skilled Scalable Services: The New Urban Bias in Economic Growth," 2020.

Engle, Robert F and Clive WJ Granger, "Co-integration and error correction: representation, estimation, and testing," *Econometrica*, 1987, pp. 251–276.

Favilukis, Jack, Sydney C Ludvigson, and Stijn Van Nieuwerburgh, "The macroeconomic effects of housing wealth, housing finance, and limited risk sharing in general equilibrium," *Journal of Political Economy*, 2017, *125* (1), 140–223.

Foote, Christopher L, Kristopher S Gerardi, and Paul S Willen, "Why did so many people make so many ex post bad decisions? The causes of the foreclosure crisis," 2012. NBER Working Paper 18082.

Ganong, Peter and Daniel Shoag, "Why has regional income convergence in the US declined?," *Journal of Urban Economics*, 2017, *102*, 76–90.

Gelain, Paolo and Kevin J Lansing, "House prices, expectations, and time-varying fundamentals," *Journal of Empirical Finance*, 2014, *29*, 3–25.

Giannone, Elisa, "Skilled-biased technical change and regional convergence," 2017.

Glaeser, Edward L and Charles G Nathanson, "An extrapolative model of house price dynamics," *Journal of Financial Economics*, 2017, *126* (1), 147–170.

Glaeser, Edward L., Joseph Gyourko, and Albert Saiz, "Housing supply and housing bubbles," *Journal of Urban Economics*, 2008, *64* (2), 198 – 217.

Glaeser, Edward L, Joshua D Gottlieb, and Joseph Gyourko, "Can cheap credit explain the housing boom?," in "Housing and the Financial Crisis," University of Chicago Press, 2012, pp. 301–359.

Goldsmith-Pinkham, Paul, Isaac Sorkin, and Henry Swift, "Bartik instruments: What, when, why, and how," *American Economic Review*, 2020, *110* (8), 2586–2624.

Greenwald, Daniel, "The mortgage credit channel of macroeconomic transmission," 2018. MIT Sloan Research Paper No.5184-16.

_ **and Adam Guren**, "Do Credit Conditions Move House Prices?," 2021.

Guren, Adam M, Alisdair McKay, Emi Nakamura, and Jón Steinsson, "Housing wealth effects: The long view," *The Review of Economic Studies*, 2021, *88* (2), 669–707.

Gyourko, Joseph, Christopher Mayer, and Todd Sinai, "Superstar cities," *American Economic Journal: Economic Policy*, 2013, *5* (4), 167–99.

Hanushek, Eric A and John M Quigley, "What is the price elasticity of housing demand?," *The Review of Economics and Statistics*, 1980, pp. 449–454.

Himmelberg, Charles, Christopher Mayer, and Todd Sinai, "Assessing high house prices: Bubbles, fundamentals and misperceptions," *Journal of Economic Perspectives*, 2005, *19* (4), 67–92.

Howard, Greg, "The Migration Accelerator: Labor Mobility, Housing, and Demand," *American Economic Journal: Macroeconomics*, October 2020.

_ **and Jack Liebersohn**, "Why is the Rent So Darn High? The Role of Growing Demand to Live in Housing-Supply-Inelastic Cities.," *Journal of Urban Economics*, 2021, p. 103369.

Jacobson, Margaret, "Beliefs, Aggregate Risk, and the US Housing Boom," 2019.

Johansen, Søren, *Likelihood-based inference in cointegrated vector autoregressive models*, Oxford University Press on Demand, 1995.

Jordà, Òscar, "Estimation and inference of impulse responses by local projections," *American Economic Review*, 2005, *95* (1), 161–182.

_ **, Moritz Schularick, and Alan M Taylor**, "Betting the house," *Journal of International Economics*, 2015, *96*, S2–S18.

_ **,** _ **, and** _ , "The effects of quasi-random monetary experiments," *Journal of Monetary Economics*, 2020, *112*, 22–40.

Justiniano, Alejandro, Giorgio E Primiceri, and Andrea Tambalotti, "Credit supply and the housing boom," *Journal of Political Economy*, 2019, *127* (3), 1317–1350.

Kaplan, Greg, Kurt Mitman, and Gianluca Violante, "The Housing Boom and Bust: Model Meets Evidence," *Journal of Political Economy*, 2019, *128* (9), 3285–3345.

Knoll, Katharina, Moritz Schularick, and Thomas Steger, "No price like home: Global house prices, 1870-2012," *American Economic Review*, 2017, *107* (2), 331–53.

Kwan, Andy CC and John A Cotsomitis, "Can consumer attitudes forecast household spending in the United States? Further evidence from the Michigan Survey of Consumers," *Southern Economic Journal*, 2004, pp. 136–144.

Lamont, Owen and Jeremy C Stein, "Leverage and house-price dynamics in US cities," *RAND Journal of Economics*, 1999, *30* (3), 498–514.

Landvoigt, Tim, "Housing demand during the boom: The role of expectations and credit constraints," *The Review of Financial Studies*, 2017, *30* (6), 1865–1902.

Liu, Zheng, Pengfei Wang, and Tao Zha, "A theory of housing demand shocks," 2019. NBER Working Paper 25667.

MacKinnon, James G, "Critical values for cointegration tests," 2010. Queen's Economics Department Working Paper 1227.

Maggio, Marco Di and Amir Kermani, "Credit-induced boom and bust," *The Review of Financial Studies*, 2017, *30* (11), 3711–3758.

Mayo, Stephen K, "Theory and estimation in the economics of housing demand," *Journal of Urban Economics*, 1981, *10* (1), 95–116.

Mian, Atif and Amir Sufi, "The Consequences of Mortgage Credit Expansion: Evidence from the US Mortgage Default Crisis," *The Quarterly Journal of Economics*, 2009, *124* (4), 1449–1496.

_ **and** _ , "House prices, home equity–based borrowing, and the us household leverage crisis," *The American Economic Review*, 2011, *101* (5), 2132–2156.

_ **and** _ , "Credit supply and housing speculation," 2019. NBER Working Paper 24823.

_ **, Kamalesh Rao, and Amir Sufi**, "Household Balance Sheets, Consumption, and the Economic Slump," *Quarterly Journal of Economics*, 2013, *128* (4).

_ **, Ludwig Straub, and Amir Sufi**, "What explains the decline in r*? Rising income inequality versus demographic shifts," *Proceedings of the 2021 Jackson Hole Symposium*, 2021.

Moretti, Enrico, "Real wage inequality," *American Economic Journal: Applied Economics*, 2013, *5* (1), 65–103.

Nagel, Stefan, "Macroeconomic experiences and expectations: A perspective on the great recession," 2012.

Nakamura, Emi and Jon Steinsson, "Fiscal stimulus in a monetary union: Evidence from US regions," *American Economic Review*, 2014, *104* (3), 753–92.

Nathanson, Charles G and Eric Zwick, "Arrested Development: Theory and Evidence of Supply-Side Speculation in the Housing Market," *The Journal of Finance*, 2018, *73* (6), 2587–2633.

Nickell, Stephen, "Biases in dynamic models with fixed effects," *Econometrica*, 1981, pp. 1417–1426.

Nieuwerburgh, Stijn Van and Pierre-Olivier Weill, "Why has house price dispersion gone up?," *The Review of Economic Studies*, 2010, *77* (4), 1567–1606.

Parkhomenko, Andrii, "Housing supply regulation: Local causes and aggregate implications," 2018.

Piazzesi, Monika and Martin Schneider, "Momentum traders in the housing market: survey evidence and a search model," *American Economic Review*, 2009, *99* (2), 406–11.

Polinsky, A Mitchell and David T Ellwood, "An empirical reconciliation of micro and grouped estimates of the demand for housing," *The Review of Economics and Statistics*, 1979, pp. 199–205.

Poterba, James M, "Tax subsidies to owner-occupied housing: an asset-market approach," *The Quarterly Journal of Economics*, 1984, *99* (4), 729–752.

Ravn, Morten O and Harald Uhlig, "On adjusting the Hodrick-Prescott filter for the frequency of observations," *Review of economics and statistics*, 2002, *84* (2), 371–376.

Roback, Jennifer, "Wages, rents, and the quality of life," *Journal of Political Economy*, 1982, *90* (6), 1257–1278.

Rosen, Sherwin, "Wage-based indexes of urban quality of life," *Current Issues in Urban Economics*, 1979, pp. 74–104.

Rozsypal, Filip and Kathrin Schlafmann, "Overpersistence bias in individual income expectations and its aggregate implications," 2017. CEPR Discussion Paper No. DP12028.

Saiz, Albert, "The geographic determinants of housing supply," *The Quarterly Journal of Economics*, 2010, *125* (3), 1253–1296.

Schaffer, Mark E, "egranger: Engle-Granger (EG) and Augmented Engle-Granger (AEG) cointegration tests and 2-step ECM estimation," 2010.

Shiller, Robert J, "Understanding recent trends in house prices and home ownership," *Proceedings - Economic Policy Symposium - Jackson Hole, Federal Reserve Bank of Kansas City*, 2007, pp. 89–123.

Taylor, John B, "Housing and monetary policy," *Proceedings - Economic Policy Symposium - Jackson Hole, Federal Reserve Bank of Kansas City*, 2007, pp. 463–476.

A Appendix Results

A.1 Robustness of Local Projection

In Figure 4, we show the results of our causal exercise are not influenced by a variety of alternative specifications of the regression. "More lags" includes additional controls for up to 6 lags of the industry divergence measure. "Pretrends" includes controls for the first and second lag of house price growth and divergence changes. "No Real Estate" uses the industry divergence measure that excludes construction and real estate industries. "GDP controls" includes controlling for the contemporaneous and the first two lags of GDP growth. "More controls" includes the GDP controls and also the contemporaneous and first-two lags of 10-year interest rates changes, the inflation rate, and income shares of the top 50 percent and the top 1 percent.

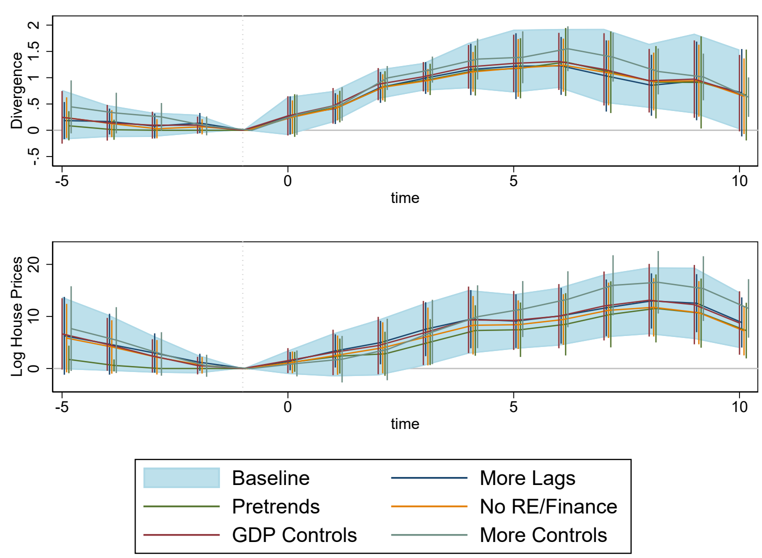


Figure A1: A local projection to innovations in the industry-driven divergence series, for regional divergence (top) and house prices (bottom). Standard errors robust to heteroskedasticity and autocorrelation (bandwidth 3).

As an additional robustness check, Figures A2 and A3 show local projections using a one-year predicted divergence shock rather than a ten-year. Our one year shock is constructed in the same way as the ten-year shock that excludes construction and real estate, except we predict divergence by interacting one-year industry growth with one-year lags of industry shares instead of doing the same for ten years. Using one-year lags rather than ten-year lags also allows us to use a consistent industry code basis for a larger number of years, so this series uses NAICS-basis GDP growth from 1988-2017. Our baseline local projection, in figure A2, does not control for any lags of growth. The local projections in Figure A3 include controls as in A1 except for "More Lags" which includes controls for three lags of the shock.

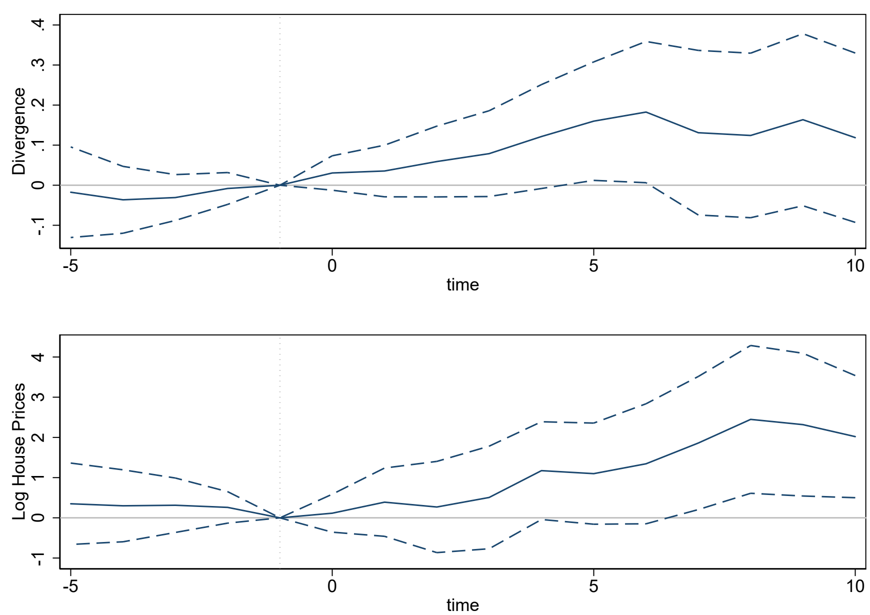


Figure A2: A local projection to the one-year industry-driven divergence series, for regional divergence (top) and house prices (bottom). Standard errors robust to heteroskedasticity and autocorrelation (bandwidth 3).

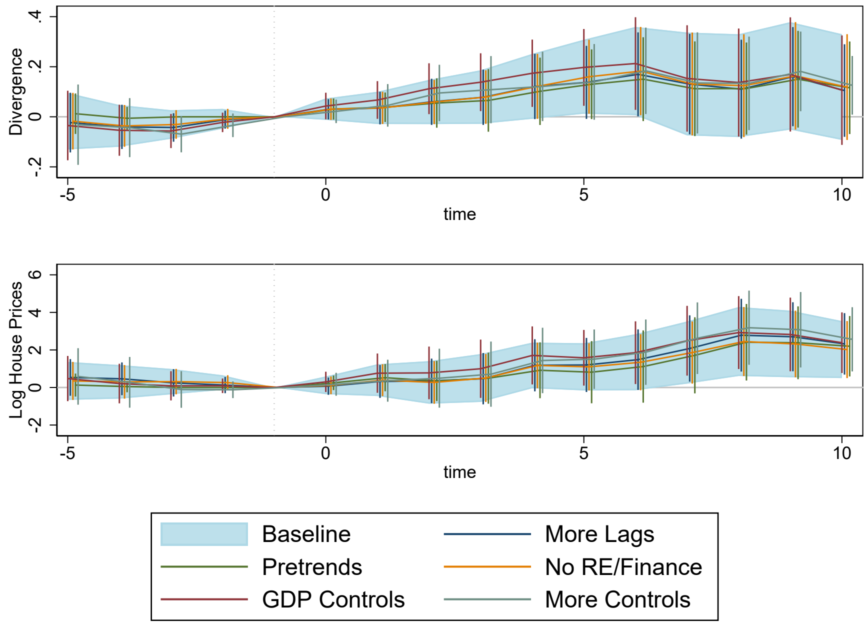


Figure A3: A local projection to the one-year industry-driven divergence series, for regional divergence (top) and house prices (bottom). Standard errors robust to heteroskedasticity and autocorrelation (bandwidth 3).

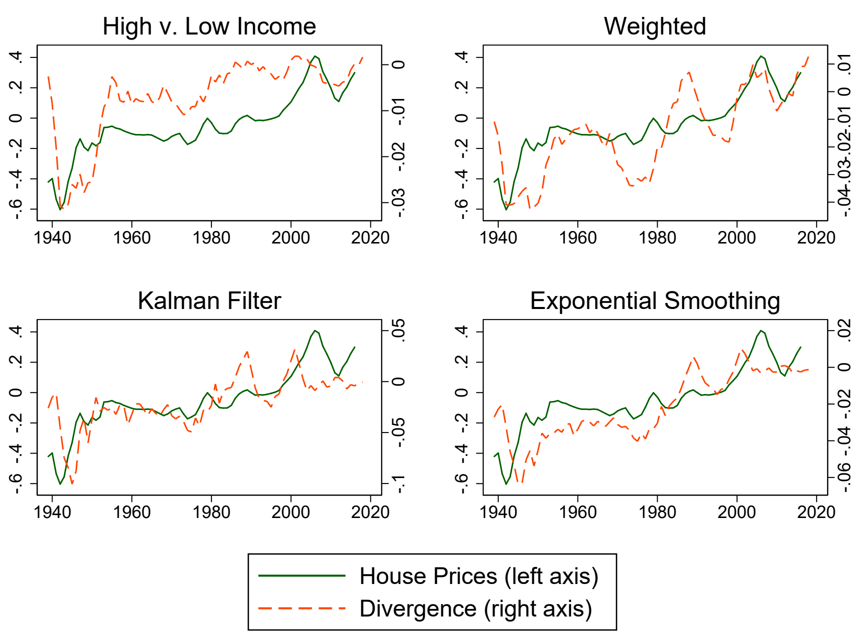
A.2 Alternative Measures of Dispersion and Divergence

Throughout the paper, we assume that agents their beliefs about divergence are based on the regression in equation (1). However, there is nothing special about that particular measure of divergence.

In Figure A4, we show several measures of divergence, as compared to house prices. They all generally show a relationship between the two. In the top panel, we show that the choice of the number of lags is not particularly important. Using 6, 8, 12, or 14 lags instead of 10 produces similar results. Changing this changes both the length that growth rates are calculated over and the baseline income that the growth rates are regressed on.

In the bottom panel, we also consider several other measures. High v. Low-Income measures the difference in growth rates between the average of the highest-income

(a) Varying the lag length of measured divergence



(b) Robust Measures of Divergence

Figure A4: Alternative Measures of Regional Income Inequality

25 states and the lowest-income 25 states. 'Weighted' is the same as the baseline except the results are weighted by lagged state GDP. The 'Kalman Filter' measure runs a regression using 1 lag instead of 10. It then assumes that each data point is a noisy signal of the "true" divergence, which is a unit root. The orange line is the best guess for the true value of divergence given the time series based on 1-year divergence. Finally, 'Exponential Smoothing' first takes a one-year-lagged log income and then takes a moving average where the weight declines by an eighth for every additional lag. Not surprisingly, it resembles the Kalman filter quite strongly.

Finally, in A5, we calculate divergence at the core-based statistical area level. We use a variety of variables on the right-hand side of the regression which calculates divergence to illustrate that differential growth levels by income, city population, housing supply elasticity, or housing price sensitivity all lead to similar patterns. These regressions are population-weighted because small cities have more variance in income growth.

In Figure A6, we show alternative measures of income dispersion and the real rent series calculated from the consumer price index. The standard deviation and interquartile range are measured across-state within-year. Similarly, the mean income minus minimum income line subtracts the log mean income of all states from the log mean income of the poorest five states.

A.3 Factor Analysis of Income Growth

We create Figure A7 by doing a Principal Components Analysis on the factors of income growth across the 49-state time series of log incomes. The figure shows the first two factors from this analysis. The second factor is highly correlated to regional divergence, and the loadings on that factor are highly correlated to income. The first

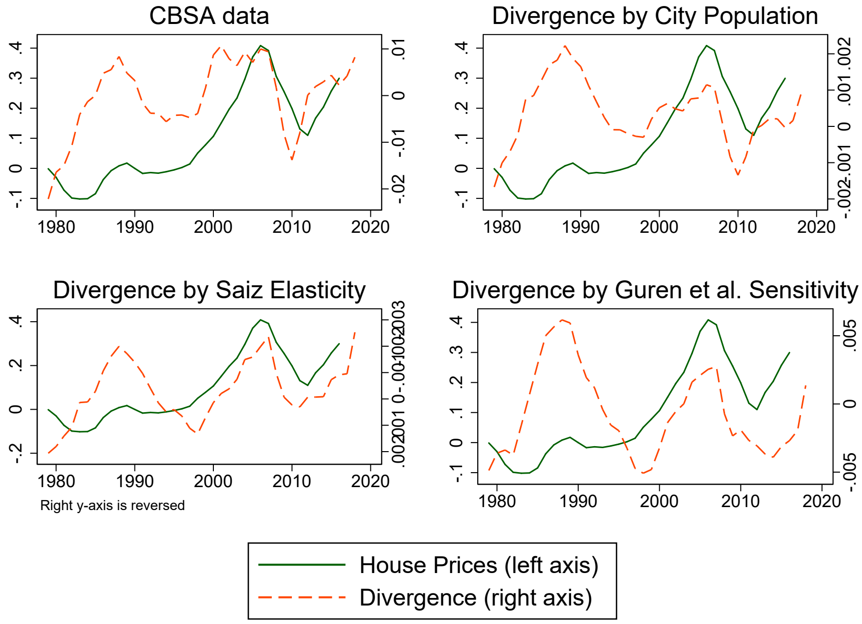


Figure A5: City-Level Divergence Measures

factor resembles national income growth. Most states have similar loadings near 1 on the first factor, which explains 85.4 percent of the variance. The second factor explains 6.4 percent. No other factor explains more than 2.1 percent of the variance.

There are minor differences between these two. Factor analysis does not allow the loadings to time-vary, as the concept of regional divergence does. And because state level incomes are less unequal in the recent past as compared to the earlier part of the sample, the second factor does not exhibit the same upward trend that divergence does.

Nonetheless, given the similarities, we feel comfortable making the claim that divergence is one of the most important things to consider when predicting state-income growth.

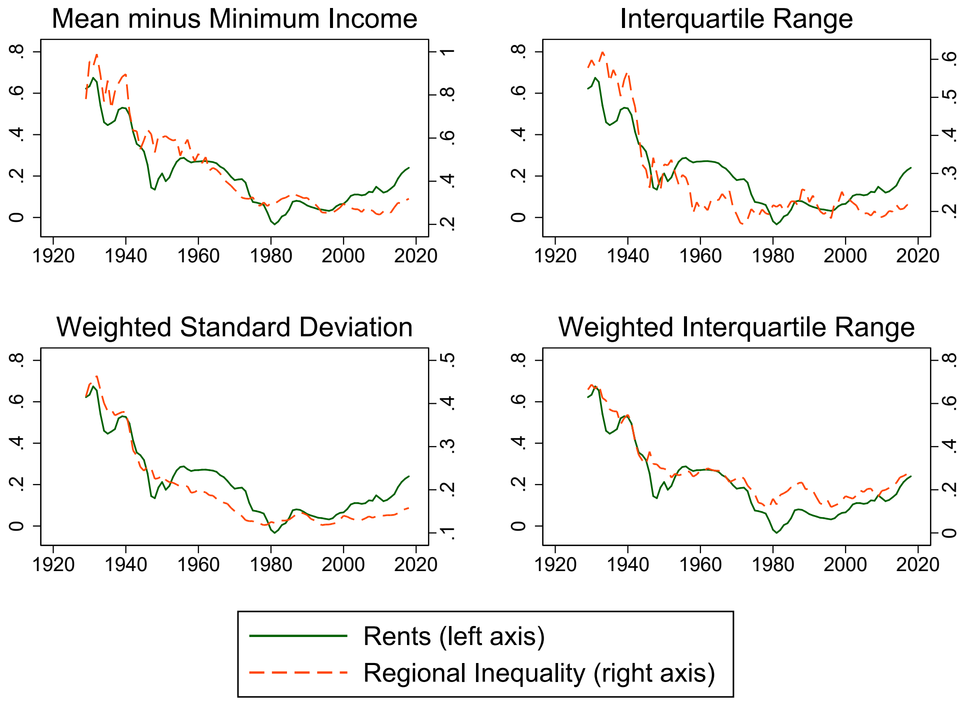


Figure A6: Alternative Measures of Regional Income Dispersion

A.4 Predicting Wages Using Lagged Divergence

In Table A1, we confirm that lagged divergence has a statistically significant relationship to future income growth using income data starting in 1945. Columns (1) and (2) show estimates that include year fixed effects, current log income and, in Column (2), log income growth. Adding our measure of regional divergence, in Columns (3) and (4), we can see reject the model of no effect of divergence with a p-value of 0.001. Divergence also has a statistically significant effect on income growth at other time horizons, and when measured using other lags of income growth. We focus on the post-WWII period because we think that wartime economic mobilization broke the link between divergence and expectations.

Our theory would predict that the regression in Column (3) should give a coefficient of 10 because growth should be 1 log-point higher for each of the 10 years.

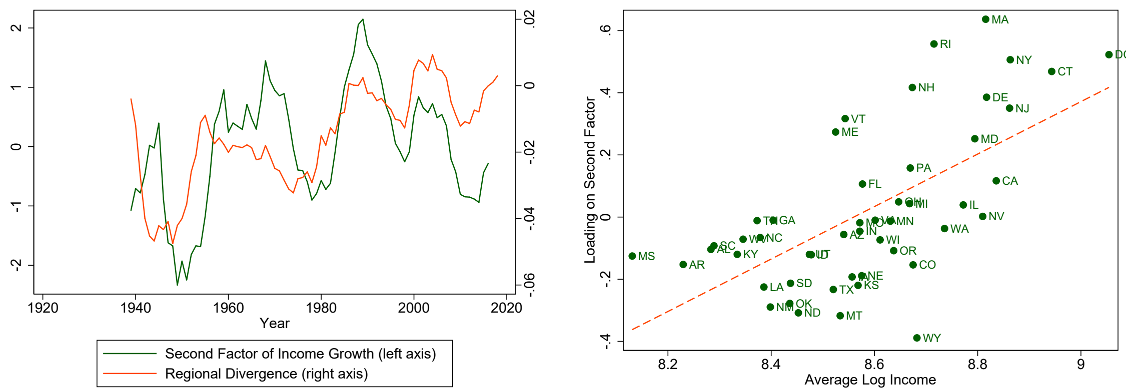


Figure A7: Factor Analysis

However, Nickell (1981) bias is a major concern in the way this regression is setup and biases the coefficient to zero. While we are unaware of a formula for the exact amount of bias in a panel regression with long-differences, it can be approximated by considering the regression of divergence, on ten-year lagged divergence. If divergence were a unit root, and we had only 7 data points (we have approximately seven decades of measured divergence), the expected Nickell (1981) bias would be $\frac{1+\rho}{T-1} = -0.333$, which we would then multiply by 10 to convert it to the right units. This back-of-the-envelope calculation suggests that Nickell (1981) bias is large in this situation, and so we do not interpret the coefficients as evidence that divergence is stationary. Further, when we compare divergence to data on expectations from the Michigan Survey, the magnitudes would suggest actual expectations move close to one-for-one.

A.5 Autocorrelation in the Divergence Process

In our model, we assume not only that agents use lagged divergence to predict future wages, but also that they use lagged divergence as a guide to future divergence. In the data, divergence is highly persistent, making this assumption a natural one. Why not simply use the most recent measure of divergence? There is some short-run noise

Table A1: Predicting Future Wage Growth

	(1)	(2)	(3)	(4)
	10-Year Future Inc. Growth	10-Year Future Inc. Growth	10-Year Future Inc. Growth	10-Year Future Inc. Growth
Log Income	-0.137***	-0.151***	-0.0919***	-0.0670***
	(0.00944)	(0.0105)	(0.0150)	(0.0155)
10-Year Inc. Growth		-0.110***		-0.183***
		(0.0225)		(0.0232)
Log Income × Divergence			2.412***	5.004***
			(0.595)	(0.687)
Observations	3136	3136	3136	3136
R^2	0.919	0.921	0.920	0.924
Year Fixed Effects	X	X	X	X

HAC standard errors (Bartlett Kernel, bandwidth 3.)

$^+$ $p < .1$, * $p < .05$, ** $p < .01$, *** $p < .001$

in divergence, so using several years' data to predict future divergence is better than using annual fluctuations. The comparison of the two time series is shown in Figure A8. One year divergence is measured the same way as ten-year divergence but is based only on the most recent year of growth.

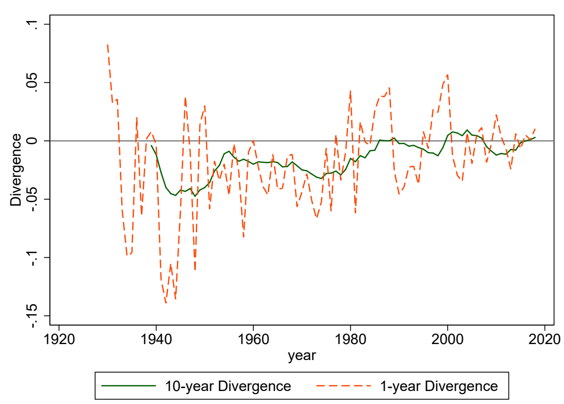


Figure A8: **The Noisiness of One-Year Divergence.**

Even though the one-year measure of divergence is quite noisy, we can still show that it has a significant amount of persistence. We use a local projection of innovations to divergence on lagged one-year divergence, shown in Figure A9. To create this figure, we estimate the following regression specification for $s = 0 \ldots 20$:

$$\log \kappa^1_{t+s} - \log \kappa^1_{t-1} = \beta_s \kappa^1_t + \gamma_s X_t \tag{14}$$

where κ^1_t is one-year divergence at time t and β_s are the coefficients of interest graphed in the figure for each value s. X_t is a vector of controls that includes κ^1_{t-1} and κ^1_{t-2}. A one-point increase to divergence between years $t-1$ and t only predicts a 0.4 point increase to divergence by years 3 or 4. This short-term mean-reversion in the first few years implies that divergence has a large noise component. At the same time, divergence also has a highly persistent component. Innovations to divergence between years $t-1$ and t predict statistically significant increases divergence as far as 20 years later.

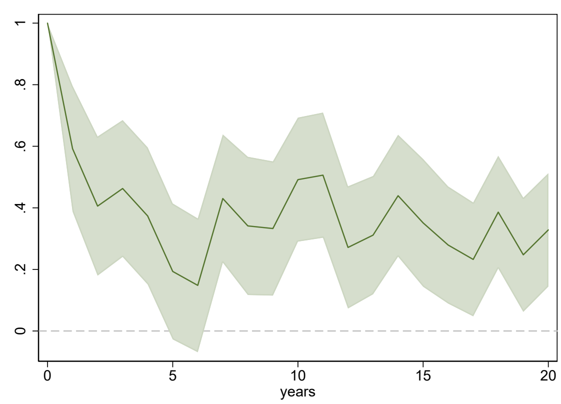


Figure A9: **Persistence of Regional Divergence.** A local projection to innovations in divergence, for lagged divergence regional divergence. Standard errors robust to heteroskedasticity and autocorrelation with a bandwidth of 3. Local projection estimated using equation (14).

A.6 Expectations

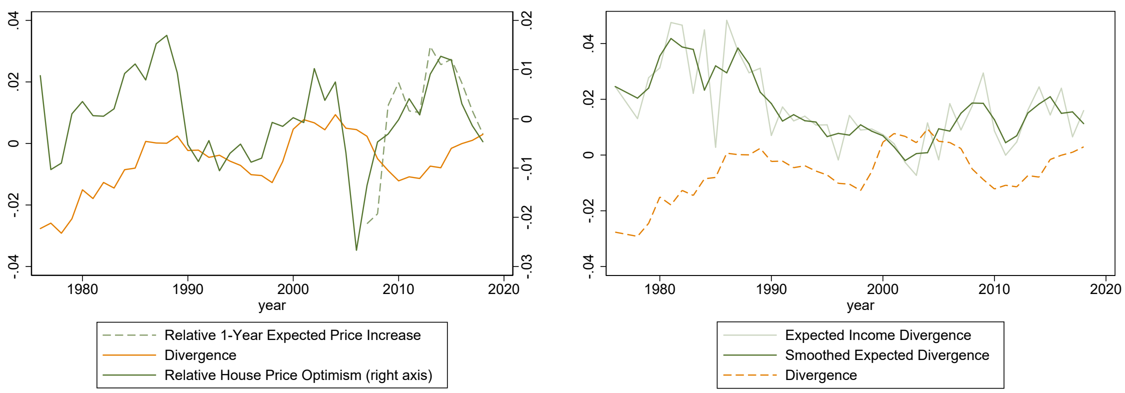


Figure A10: **Divergence in Expected Local Prices.** The Expected Divergence lines are coefficients of a regression of 1-year expectations on income growth from the Michigan Survey of Consumers on log income, weighted by survey weights. House price expectations are shown on the left and personal income expectations are shown on the right. Smoothed Expected Divergence is a three-year moving average of the Expected Divergence line. Divergence is the line described in Figure 2.
Source: Michigan Survey of Consumers and calculations as described in the text.

Our theory predicts that price expectations and divergence should be correlated. When divergence is higher, price expectations for high-income regions should be higher. The same thing is true specifically for house price expectations.

We create a measure of local price optimism similar to the survey's measure of price expectations. Ideally, we would have survey data measuring expected house price growth in each state over time. To the best of our knowledge, such data is only available for the very recent past, so we show expectations data since 2007. To create a measure of house price optimism that extends further back, we use a methodology similar to that implemented by Michigan Survey of Consumers to measure price expectations. For each state and year we calculate the percentage of respondents who report a belief that house prices will increase and subtract the percent that believe prices will decrease.

We regress this measure on log income in each year to create a measure of the relative beliefs held by agents in higher-income areas. The left panel of Figure A10 shows this relationship. Beliefs slightly lead actual divergence, but otherwise the series line up closely.[64]

We would also expect divergence in personal income expectations to be correlated to divergence. This relationship is shown in the right panel of A10 and is somewhat noisier than the other measures. This is likely because the question refers to their own income, not average incomes in their area, so there is naturally much more variance. The time series also shows the same drop in the early 2000s as price expectations do.[65]

A.7 State-Level Model

Figure A11 shows estimates from the state-level model. To create this figure, we estimate specification 1 using a panel of county income for each state. This yields state-by-year convergence estimates. We use the state-by-year convergence estimates to understand the relationship between state-level house prices and state incomes.

[64] The regression relating divergence and smoothed relative price optimism, controlling for a time trend, is positive but not statistically significant ($t = 0.56$) using heteroskedasticity- and autocorrelation-robust standard errors (Bartlett Kernell bandwidth 3). Lagging expectations by two years, the relationship is significant at the 5 percent level (t=2.43).

[65] Controlling for a year trend, the regression relating divergence and expeced divergence is statistically insignificant ($t = -0.54$) using heteroskedasticity- and autocorrelation-robust standard errors (Bartlett Kernell bandwidth 3).

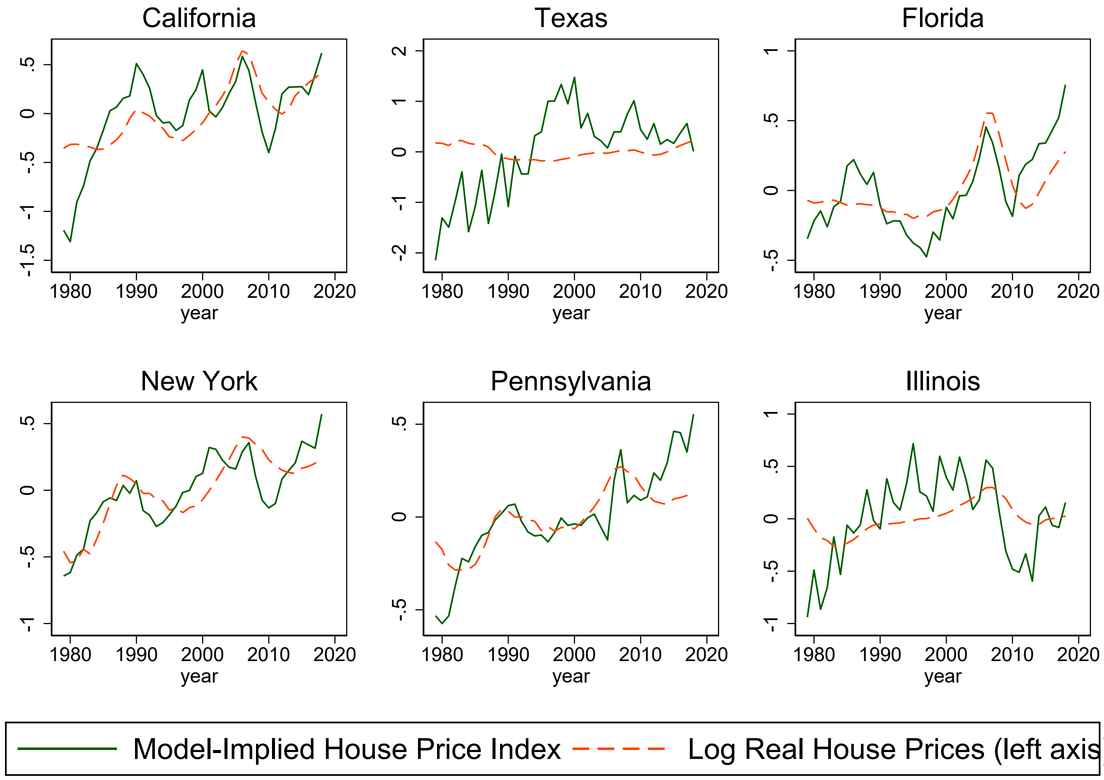


Figure A11: Model-Implied House Prices from state-level model vs actual house prices, six largest states by population.

A.8 Income and Sensitivity

In Figure A12, we show a positive correlation between income and measures of house price sensitivity or volatility. Our theory makes the prediction that local house prices should be more sensitive to national swings in high-income areas, so we wish to show the relationship to other common measures already in the literature. Most prominently used is the elasticity measure of Saiz (2010), which is often interacted with national trends or interest rates as an instrument for house price changes. This is strongly negatively correlated to income. Recently, Guren et al. (2021) have created a measure of sensitivity to instrument for house price changes. This is positively correlated to income. Finally, we also show that the volatility of house price changes is positively correlated to income.

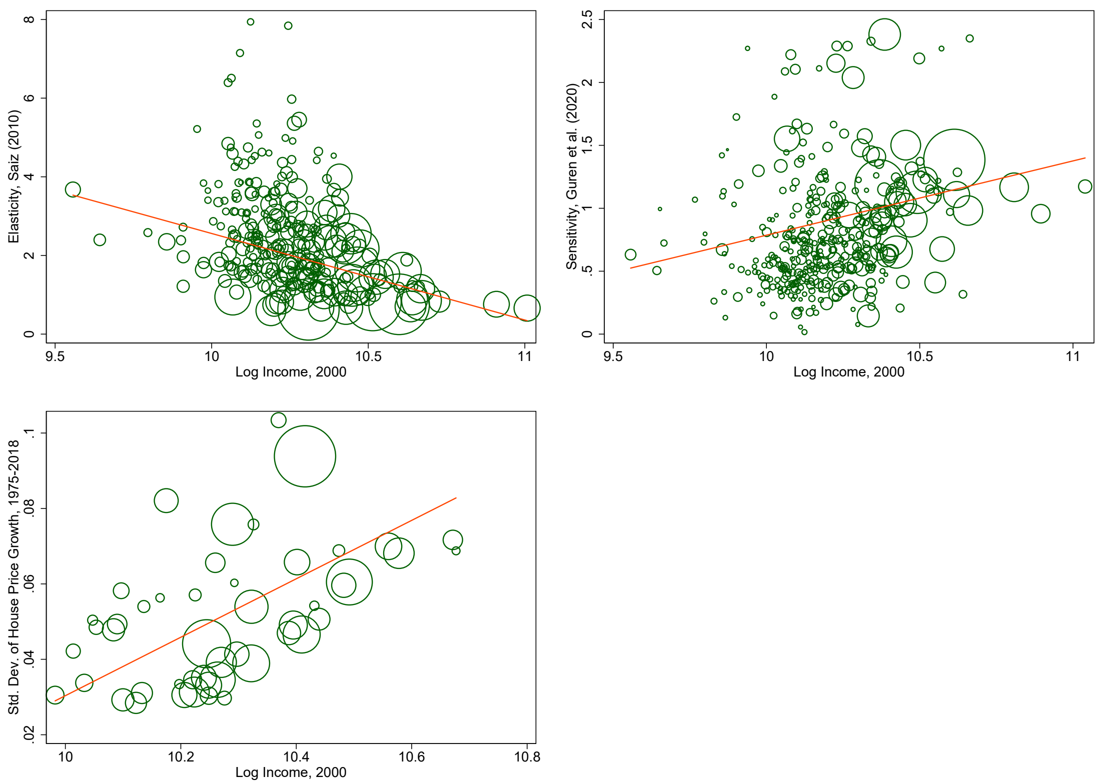


Figure A12: Measures of housing sensitivity versus income. Top left: Elasticity from Saiz (2010). Top right: Sensitivity from Guren et al. (2021). Bottom: house price volatility.

A.9 Sensitivity of Income

In Figure A13, we look at which states have income most correlated to divergence. We refer to this as sensitivity because we calculate it in a similar way to how we calculate house price sensitivity in Section 4. It comes from the following regression

$$\log w_{i,t} - \log w_{i,t-10} = \beta_i \kappa_t + \alpha_i + \epsilon_{it}$$

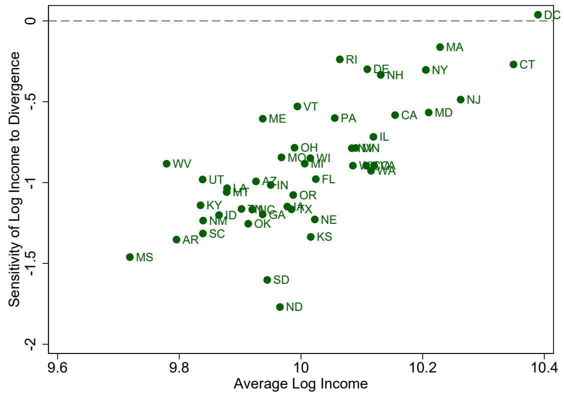


Figure A13: The sensitivity of income to regional divergence

where w_{it} is the real per capita personal income of state i at time t and κ_t is regional divergence. β_i captures how much higher the 10-year growth rate of a state is when divergence is higher. We then plot the β_i against average log income in Figure A13.

The positive relationship between β_i and income is not surprising given the definition of divergence. However, the level of β_i was not *ex ante* obvious. Here, it turns out that the poor states have income growth negatively correlated to divergence, while the rich states are less correlated. The implication is that it is the poor states whose income growth drives divergence. So when poor states grow quickly, divergence is low, and when poor states grow slowly, divergence is high.[66]

A.10 Housing Supply

In the main text of the paper, we avoided taking a stand on the housing supply function because we did not need to in order to match prices and rents. In this appendix, we show that a reasonable housing supply function can deliver realistic population movements.

Housing supply differs across space and time. Saiz (2010) documents differential

[66] In general, the variance of income growth in poor states is higher, so that would be one reason to expect this result.

housing supply elasticities based on a variety of factors. Ganong and Shoag (2017) document how much harder it has gotten to build housing over time. On the other hand, if we were to specify a housing supply function that could freely vary over both time and space, then our model would have no predictive power at all when it came to predicting population movements.

The following functional form seems like a reasonable compromise:

$$\Delta \log H_{it} = \sigma_i \log p_{it} + \alpha_i + \alpha_t + \epsilon_{it} \tag{15}$$

where the growth rate of housing quantities is governed by a location specific elasticity and intercept, and we allow the amount of housing built to also vary with a year-specific shifter, to reflect Ganong and Shoag (2017)'s findings that housing is getting more difficult to build.

What we think is particularly helpful with this specification is that it still predicts that higher housing prices should lead to higher housing construction in the cross-section and also accounts for the fact that there is differential housing supply elasticities across space.

There are also two ways to potentially test this housing supply function. The first is to use our state-level panel, and see what elasticities would be consistent with the rest of our model, at the state level.[67] We can then see if those elasticities have a reasonable relationship with income. The results of estimating this equation are presented in Figure A14. While the results are noisy, and some of the states are even estimated to have negative elasticities, there is a clear negative relationship between the model-consistent elasticity and state income. The poorest states are way more elastic than the richest states.

[67] We would not suggest using these elasticities as estimates of the actual elasticity. We are only interested if there exist a set of elasticities consistent with our model and observed population flows.

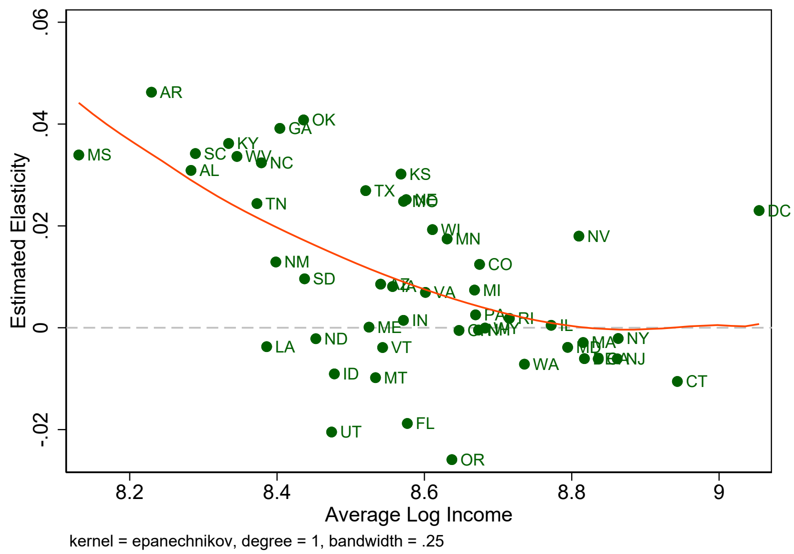


Figure A14: Estimated elasticities. Line is a smoothed fit line, created using a kernel-weighted local linear regression with epanechnikov kernel of bandwith 0.25.

The other way would be to use the elasticities that have previously been estimated by Saiz (2010), and see if they predict population growth. In this case, we can assume that the short-run elasticities of the model are a linear transformation of the Saiz (2010) elasticities, which are long-run elasticities.

We estimate the regression:

$$\Delta \log H_{it} = (A\sigma_i + B) \log p_{it} + \alpha_i + \alpha_t + \epsilon_{it}$$

For this exercise, we only use data starting in 1969, when we have data on incomes and populations by county.

We estimate a positive A across several specifications. For housing growth, we take the population growth rate, and add the income growth rate, and subtract the model-implied rental growth rate, as that is the housing growth rate implied by Cobb-Douglass demand in our model. We also look just at population growth rates, to show

Table A2: Predicting Housing Growth

	(1) Pop Growth	(2) Pop Growth	(3) Housing Growth	(4) Housing Growth
Model House Prices	0.00493		-0.0136**	
	(0.00408)		(0.00424)	
Model HP X Elasticity	0.00418***	0.00501***	0.00405***	0.00177*
	(0.000953)	(0.000686)	(0.00101)	(0.000683)
MSA FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	13181	13181	13181	13181
R^2	0.517	0.516	0.806	0.805

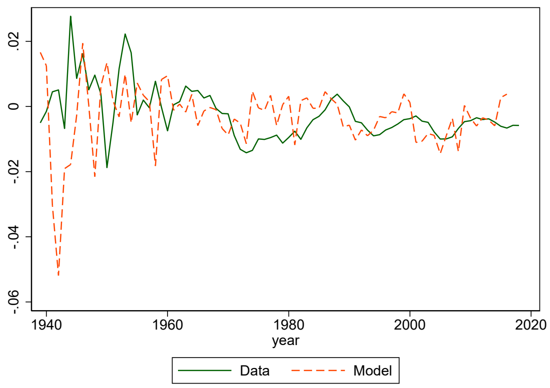
Standard Errors clustered by MSA

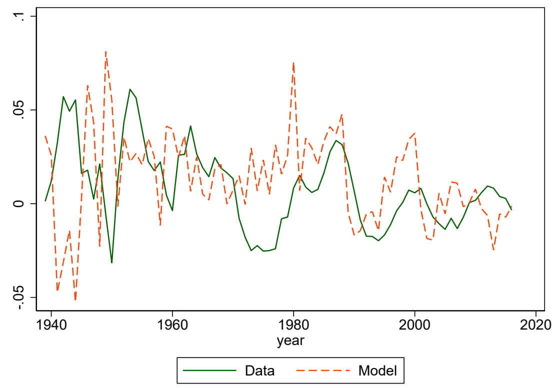
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

that the results are driven by those. In a couple of the specification, we constrain $B = 0$ in order to show that the results do not depend on B.

Overall, our takeaway from these two exercises is that the population growth data, our model's predictions regarding housing prices, and the facts that we know about housing supply elasticity are all internally consistent. When we take the population growth and the house prices, and use them to estimate elasticities, we get sensible results: that the richest parts of the country are quite inelastic, and the poorer parts are significantly more elastic. Critically, this matches our assumption that the poorest states are quite elastic. Conversely, when we take the elasticities from Saiz (2010) and the house prices from our model, and use them to estimate population growth, the data supports the predictions of the model.

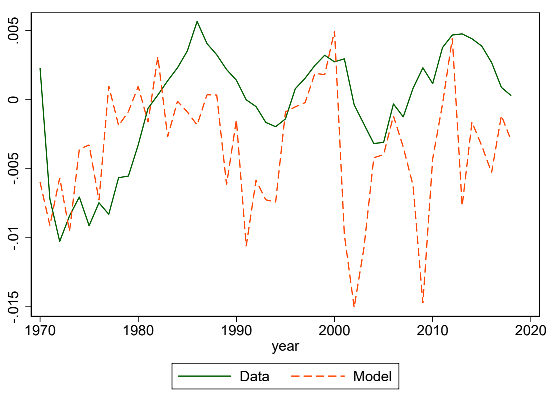
Our final step is to show that the estimated housing supply functions in Figure A14 lead to realistic population movements. We take our estimates of the fixed effects and the housing supply elasticities from (15). Then, using the predicted values from that regression, we can estimate the implied population growth by state and year. And finally, we compare the relationship between income and population growth, by





(a) Relative Population Growth, High vs. Low Income, state-level

(b) Relative Population Growth, Linear Regression on Log Income, state-level



(c) Relative Population Growth, High vs. Low Income, MSA-level

(d) Relative Population Growth, Linear Regression on Log Income, MSA-level

Figure A15: The predicted population growth of high and low income states, model and data.

year, in the model and the data.

We look at two cuts of the simulated data and actual data. The first way is the same as we do in Section 4.6. We divide the country into a high-income and a low-income region and we compare the population growth rates. That is shown in Figure A15a. We also run a linear regression in each year, of the population growth rate on log income, and plot the coefficient in Figure A15b.

The fit is not perfect in either figure, but the general patterns are similar. Especially in recent years, the fluctuations are fairly similar, although the model seems to lead the data by a few years. In the earliest years, there are some very large fluctuations during World War II, and so we would take those changes with a grain of salt.[68] The biggest miss is the late 1970s, which featured population growth in poorer regions, which the model misses. But overall, we think this is supportive of our story.

We do the same thing using the predicted population movements when using the Saiz (2010) elasticities, in Panels (c) and (d). Here the figures are still noisy, but give a similar general impression.[69]

B Construction Costs and Interest Rates

In this appendix, we incorporate dynamic interest rates and construction costs into the model. The main goal is to better explain the house price movements in the 1980s and 1990s. Our baseline model overestimates the rise in house prices, and misses the boom in the 1980s. These two additional ingredients help resolve the issue.

The changes we make to the model are straightforward. First, instead of having a constant price of construction, we use the production price index of construction materials, deflated by CPI. This has fallen over time, so we add 0.2 log-points per year to account for rising prices due to labor. Second, instead of using a constant $R = .05$, we instead use a changing interest rate. There are several concerns here. First, the correct interest rate to use is not obvious. Because it is a long-term rate, we use the 10 year rate from Knoll et al. (2017). Second, we do not have a measure of inflation expectations that goes far enough back to account for real rates (for example, the Michigan survey begins in the late 1970s). We also do not have measures over

[68] In fact, the correlation between the data and the model is slightly negative, largely due to the fluctuations at the beginning.

[69] The correlation in both figures is about 0.2.

the changing depreciation rates or changing property taxes that would be necessary to calibrate R. We assume that most of the variation in R is due to changes in the nominal rate, and we add 2 percent to account for taxes and depreciation net of inflation expectations. We assume agents in the model expect the current interest rate to last forever.

Using these time varying series, we then calculate house prices using the formula from our model:

$$\log p_{it} = \log \bar{p}_t + \frac{1}{\alpha} \frac{R_t}{R_t - \kappa_t} (\log w_{it} - \log \bar{w}_t) \tag{16}$$

The only difference here is the time subscripts on the R and the $\bar{p}$. In our model, the level of house prices does not depend on the expectations of future construction costs, so we do not need to take a stand on agent's beliefs regarding those.[70]

As we argue in the main text, a change in R_t has a small effect on house prices when κ_t is near zero, but it does dampen the change in house prices when κ_t changes. Because divergence does change in the 1990s when interest rates are high, the model without dynamic interest rates is going to overstate the boom.

The role of construction costs is also straightforward. They increased significantly in the late 1970s, so could help explain why house prices increased then when divergence did not.

The results of augmenting the model are shown in Figure A16. As before, the model can account for most of the large swings in house prices in the post-World-War-II era, including the boom in the 1950s, and the boom in the early 1990s, and the boom-bust-boom of this century. Having dynamic construction costs and interest rates help match the boom in the late 1970s which the model had previously failed

[70]This is not true of rents, which would depend on agent's expectations of future construction costs.

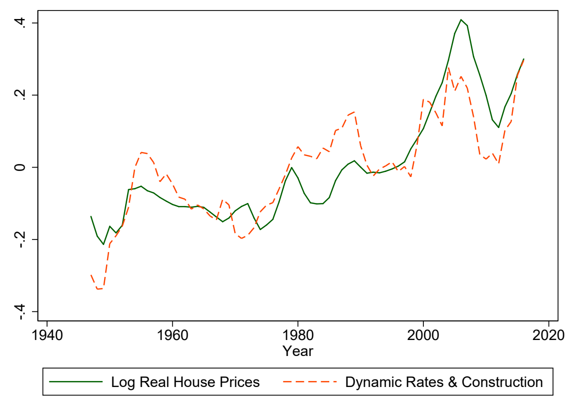


Figure A16: The Augmented Model versus Actual House Prices.

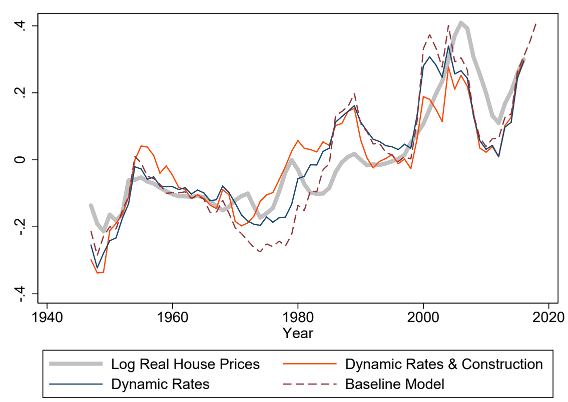


Figure A17: The Augmented Model versus Actual House Prices. Breaking down the role of interest rates and construction.

to match.

To see whether it is construction costs or interest rates that are quantitatively more important, we break down the role of each in Figure A17. The dashed red line is the model with constant interest rates and construction costs. The blue line includes dynamic interest rates but constant construction costs, and the orange line is the line from Figure A16, with both dynamic interest rates and dynamic construction costs. All three models are fairly similar except around 1980, and both dynamic interest rates and dynamic construction costs both play a role in explaining the late

1970s boom.

Interestingly, the distance between the orange and blue lines in the early 2000s may suggest that construction costs can help explain some of the timing of the 2000s boom as well.

Throughout the time period, it is clear that most of the movement in the model with both dynamic rates and construction costs is similar to the movement in the baseline model, in which most of the movement is explained by changes in regional divergence. While interest rates and construction costs are helpful to improving the model on the margin, the main driver of house prices is divergence.

C Data

C.1 Rents and Incomes

Our national-level rent measure comes from the Bureau of Labor Statistic (BLS)'s Consumer Price Index (CPI) and is deflated by the overall index. We create a city-by-year rent measure using Zillow data on rents spliced with the BLS index for 21 cities.

Income at the state level is the per capita personal income as measured by the Bureau of Economic Analysis (BEA). To measure personal income by CBSA, we calculate the weighted average personal income in each CBSA using county-level data from the BEA.

C.2 Migration and Population

We use intercensal population estimates from the U.S. Census Bureau until 2010 and postcensal estimates thereafter. We calculate total migration (domestic + international) in each year. Data from 1990 is missing so we interpolate this from the surrounding years.

C.3 House Prices

Historical national house prices come from Knoll et al. (2017) and are deflated by CPI.

To measure state- and CBSA-level house prices, we use a combination of Zillow data and the FHFA house price index. Ideally, we want a quality-adjusted price that is consistent across space. The closest thing that we know of is Zillow's measure of median home value per square foot, which starts in 1996. We extend this back by splicing it with the FHFA house price index for states.

C.4 Expectations

We use anonymized data from the Michigan Survey of Consumers that contains state identifiers for the years 1976-2018. Here we describe the process we use to create state-by-year indexes of house price optimism, income expectations and inflation expectations. Then we describe the process we use to create Figure 5.

To create a measure of local house price optimism, we follow a method similar to what the Michigan Survey of Consumers uses to create indexes of house preferences. First, we calculate the percent of respondents reporting that it is a good time to buy housing because prices will go up (values of 13 or 46 for HOMRN1 or HOMRN2); and the percent reporting that it is a bad time to buy because prices to go down (values of 53 or 86 for HOMRN1 or HOMRN2). These are calculated using survey weights. Our index of price beliefs is the difference between these two percentages. We create a year-by-state income expectations index in three steps. First, we censor values of expectations that are not between -25 and 25. Second, we take the average income expectations for people with a) positive expectations and b) negative expectations in each state and year. We use the averages in the second step to impute the expectations of people who report positive or negative views but do not report specific values. Third, we calculate state-by-year averages. All averages use survey weights.

To calculate price expectations, we truncate values between -5 and 30 and then use non-missing values to impute expectations of people who report upwards or downwards beliefs but do not report specific values.

The series shown in Figure 5. are created by measuring, in each year, how the values of each series vary based on regional incomes. We do this by estimating the regression

$$\log Y_{it} = \beta_t \log w_{it} + \gamma_t + \epsilon_{it}$$

where Y_{it} is the expectations index. The series in Figure 5 are the β's from each year.

C.5 Shift-Share Regional Divergence

This appendix describes the creation of the shift-share divergence measures and shows the robustness of our results to alternative data choices.

We create a shift-share predicted divergence measure in two steps. First, we create a shift-share measure of predicted per capita personal income growth at the state-by-year level. Second, we calculate regional income divergence by regressing this measure on lagged per capita personal income. The shift-share measure of predicted per capita personal income growth requires several data choices which we describe below. We also discuss similar results for series created using alternative choices about which data sources to use.

The available data varies over time. Whenever possible, the measure is created by multiplying the share of personal income coming from each industry (measured at the state level with a ten-year lag) by ten-year national growth of that industry's GDP. Then we sum over all industries in the state.

1958-1997 (SIC Basis): State-level personal income industry shares by industry are available from 1969 onwards, so for the pre-1979 series we use the 1969 shares. Industry growth is measured as GDP growth per employee nationally, available from 1948-1997, hence our series extends from 1958-1997. For robustness, we also show results where industry growth is measured using growth in personal income per employee by industry. Since this is available 1969-2000, this supplemental series is created from 1979-2000. The four tables used to create these measures (national FTE by industry, national VA/GDP growth by industry, state-level personal income by industry and national personal income by industry) are available on an SIC basis from the BEA. Using FTPT instead of FTE employment, we find nearly indistinguishable results. The tables are matched by aggregating industries to the most detailed level that match across tables, typically two-digit or three-digit SIC industries. For the handful of industries where employment growth is not available, we approximate industry growth per employee by dividing industry growth by growth in the national workforce of all industries.

1998-2017 (NAICS Basis): State-level personal income shares by industry are available from 2001-2017, so we use 2001 shares before that year. National-level industry growth data is available on a NAICS basis from the BEA (after 1997, it is collected on a NAICS basis, and before 1997, the BEA creates this by reclassifying SIC-basis data). We match industry-level employment (FTE, but FTPT results are indistinguishable) with industry-level GDP data to measure growth per employee. We

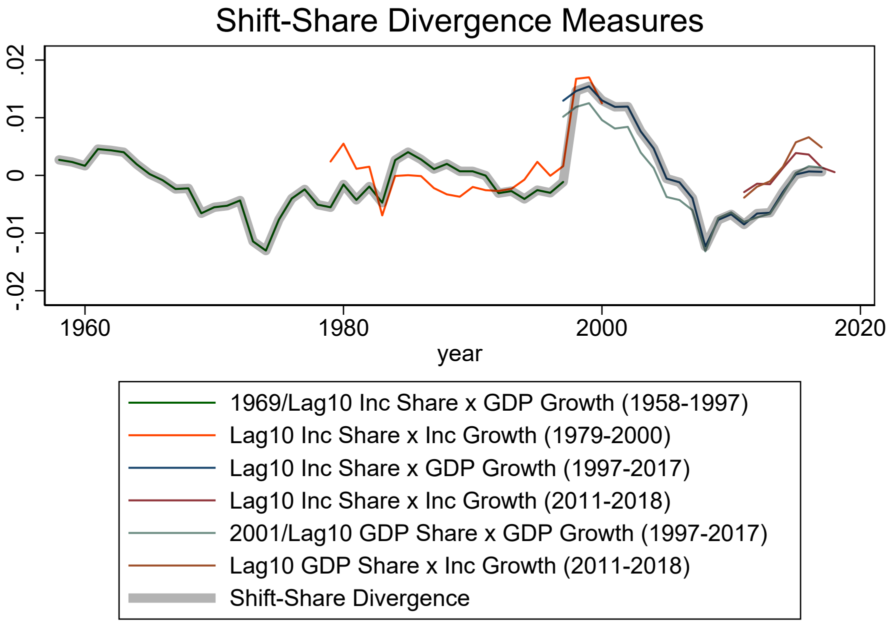


Figure A18: Shift-Share Divergence Measures, primary series and alternative series.

also create alternate series that measure state-level GDP shares by industry rather than personal income shares, and national growth in personal income per employee rather than GDP growth. Combining the two national-growth series and the two state-level industry shares series yields a total of four possible series. To match the BEA's NAICS-basis data on employment, personal income and GDP by industry, we use high-level NAICS industries which we match by hand across tables. We exclude industry 55 (Management of Companies) since FTE employment is not available for this industry. This yields a total of 19 industries that we match across tables.

Figure A18 shows the series we use along with alternative series created using other measures of industry shares and industry growth.

To study the contribution of particular industries to the shift-share divergence measure, we selectively replace their national growth rate with the average growth rate of income in general. Then we recalculate the predicted divergence measure.

The figure below shows how predicted divergence changes when we set growth equal to national growth for industries related to professional services. We define this to be NAICS 2-digit codes 51-52 and 54-71; and SIC codes 62-65, 67, and 73-86.

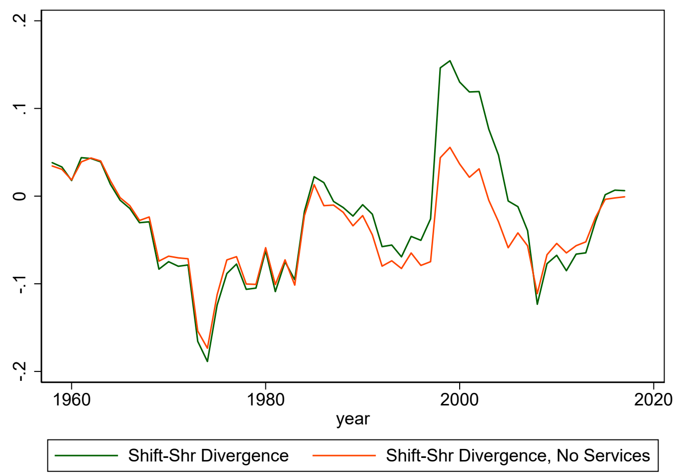


Figure A19: Industry-Predicted Regional Divergence, and With and Without Professional Services

One of the main concerns about this exercise is that real estate and construction might actually be driving the divergence. To verify that these sectors do not drive the results, we exclude both construction and real estate finance from the construction of the shift-share, and show that in Figure A20. Given these lines are hardly distinguishable from one another, we conclude that trends in the real estate sector are unlikely to be driving the co-movement between regional divergence and house prices.

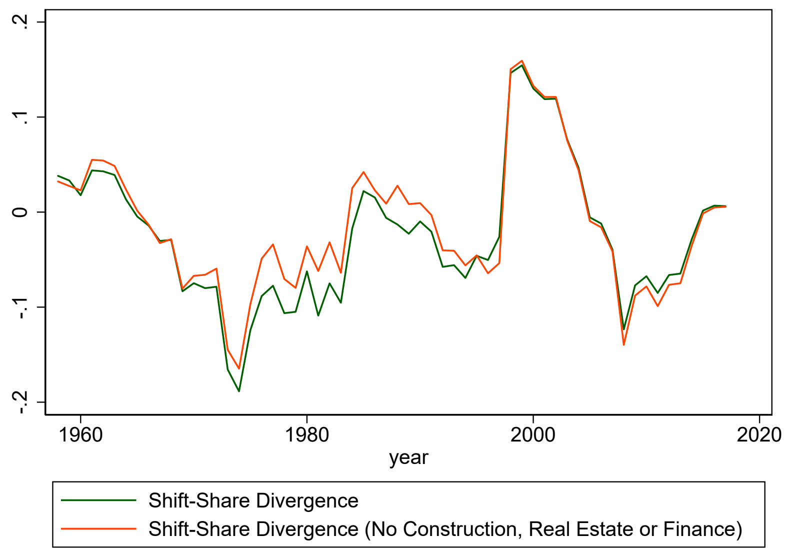


Figure A20: Shift Share Divergence Prediction, Primary Measure and Without Real Estate. The shift share measure without real estate is created in the same way as the primary measure, but excludes the real estate finance and construction sectors when calculating state industry GDP shares.