The Short- and Long- Run Effects of Remote Work on U.S. Housing Markets*

Greg Howard† Jack Liebersohn‡ Adam Ozimek§

June 6, 2023

Abstract

Remote work has increased the demand for housing and changed the demand for the location of that housing. Because housing supply is heterogeneous across space and more elastic in the long-run, the effects on rents and populations may differ over time. We use the lens of a spatial housing model with heterogeneous housing supply elasticities to identify the housing and location demand changes from 2020-2022, and show that the same shocks will have different effects in the long run. Even though rents and prices increased significantly in the short-run, we estimate that in the long-run, increased housing demand will increase rents by only 1.8 percentage points, and that changing location demand will decrease rents by 0.3 percentage points, with a more negative impact on cities in which CPI is measured and cities that were initially expensive.

JEL Codes: R31, R23, E31

Keywords: housing markets, housing affordability, labor mobility, regional inequality

*Thanks to Connor O'Brien for excellent research assistance. Thanks to Jeff Tucker and Zillow for providing county-level rents data (ZORI). Thanks to Jan Brueckner, Andra Ghent, Albert Solé Ollé, Andrii Parkhomenko, Michael Reher, Gregor Schubert, Elisabet Viladecans-Marsal and seminar participants at the University of California-Irvine for helpful comments. Greg and Jack would like to thank Economic Innovation Group for financial support of this research.

†Department of Economics, University of Illinois, 1407 W. Gregory Dr., Urbana, IL 61801, USA. glhoward@illinois.edu

‡Corresponding author. Department of Economics, University of California - Irvine, 3279 Social Science Plaza, Irvine, CA 92617, USA. liebersohn@gmail.com.

§Economic Innovation Group

1 Introduction

This paper studies the effects of remote work on housing affordability and inflation. We argue that the long-run impacts of remote work on housing affordability are likely to be different than the short-run changes because housing supply is more elastic in the long-run and heterogeneous across space. We consider two ways that remote work changes housing demand. First, demand shifts away from the central business districts of large cities, where housing is inelastically supplied. Because relative demand increases in areas with inelastic housing supply, housing costs fall on average in the long run. Second, remote work increases the demand for space. This force raises the cost of housing in both the short and long run, but with smaller long-run effects because housing supply is more elastic.

Understanding the long-run effects is important in part because the short-run effects of remote work have been so large. Real rents in the United States rose by eight percent and real house prices rose by over twenty percent from 2020 to 2022, and these changes have been heterogeneous across space. A growing body of literature has argued that many of these short-run changes are due to remote work.[1] If the long-run effects are different than the short-run effects, as we argue, this means that there are still substantial changes to come for housing markets.

We study the net effect of these forces using a model of the U.S. housing market designed to capture housing demand in the short- and long-run, as well as differences in short- and long-run housing supply elasticity. Building on Howard and Liebersohn (2021), households have demand for a quantity of housing and demand for living in a location, in this case, a county. Locations have a site-specific long-run housing supply elasticity. We derive formulas for rent and population changes in each location as a function of shocks to housing demand and the demand to live in each location, given supply elasticities and the two demand elasticities.

We use this model to calculate the long-run effects of remote work in two steps. We first invert the model to calculate the housing demand shocks and location demand shocks caused by remote work using observed rent and population changes from 2020-2022. Backing out the shocks requires assumptions about housing demand elasticity which we take from the literature. Importantly, we assume that the housing supply is inelastic in the short run. To confirm that our location demand shocks are indeed related to remote work, we validate that the shocks for each county are correlated to local remote work measures from Dingel and Neiman (2020).

[1]See for example, Parkhomenko (2020) and Davis, Ghent and Gregory (2021), who also build spatial equilibrium models to study the rise of remote work.

In the second step, we consider a long-run version of the same model where housing is supplied with a long-run elasticity specific to each region. We then consider the housing and location demand shocks from the first step and ask what effect these shocks would have on aggregate rents in the long run. We show in the model that there are two forces that govern house prices and derive simple formulas for them. The first force is the effect of the changing demand for where people want to live, which we call the *location demand* channel. We calculate the magnitude of the location demand channel by feeding in the location demand shocks from the first step, assuming that the housing supply elasticity in each region equals its long-run historical levels. Under our preferred calibration, the shift in location demand to more elastic areas will cause a 0.3 percentage point decline in rents in the long run.[2]

In addition to changing where people wanted to live, remote work raised demand for housing in general which caused rents to rise. We call this second force the *housing demand* channel. Similar to the location demand channel, we calculate the size of the housing demand channel by feeding the implied housing demand shocks into formulas derived from the long-run version of the model. The estimates shows that the long-run effects of greater housing demand on rents are less than one-half of the short-run effects. The precise amount of the housing demand shock is somewhat uncertain, because housing demand rose from 2020-2022 for reasons other than remote work.[3] Under the conservative assumption that the entire increase in demand for housing quantity was due to remote work, we estimate that the long-run impact of the housing demand channel is a 1.8 percentage point increase in rents. Since the short-run effect is even larger, this implies a decline of about 5.2 percentage points from the short-run to the long-run.

The net effect of remote work on housing costs is the sum of the effects coming from housing demand and location demand. Taken together, the long-run effect on real rents will be about one-fifth of the short run effect on average. We also show that the net effects of remote work vary across space. For the five most expensive U.S. cities, the net effect of remote work will be a fall in housing costs.

Our results also have implications for the housing component of the consumer price index (CPI). Because the CPI is a measure developed for urban consumers, the rental component of CPI is calculated for 87 urban areas, not the entire country (Bureau of Labor Statistics, 2013). These urban areas experienced a relative decline in location demand versus the rest

[2]In Section 6.4, we show that our 3-period model of rents is nested in an infinite-horizon model that includes house prices. The long-run implications for rents and house prices are the same in those models, so when we discuss implications for the long-run effects on rents, those are the same as the long-run effects on house prices.

[3]Other reasons include stimulus payments, low interest rates, and greater value of home consumption due to the pandemic.

of the country, so both the short- and the long-run effects of remote work on CPI-rents are more negative than the effects on the average rent. We calculate the effect on the housing component of CPI by considering the model's implications for the areas that are measured for CPI-rents, finding that the effect of location demand on CPI counties is about -1 percentage points.

The housing demand channel is an example of the Le Chatelier (1884) principle in that the long-run housing supply is more elastic than the short-run, leading to smaller effects on prices in the long-run. The location demand channel has a bigger impact because the average housing supply becomes more elastic when people choose to demand housing in places that are more elastic. For this channel, the distinction is not about the short- versus the long-run, but rather the location that people are choosing.

Two stylized facts motivate the model assumptions and structure. The first stylized fact is that real rents grew by 8 percent, with most of the change occurring over a six-month period in mid-2021. The rise in real rents appears in a variety of data sets and was a major driver of inflation over the same time period. The second stylized fact is that populations and rents grew in areas where housing supply has historically been more elastic. Looking within urban areas, populations fell and rents grew by less in center cities, as compared to the suburban and exurban ring surrounding them. Rents and populations also grew less in the surrounding countryside, leading to what Ramani and Bloom (2021) call the "Donut Effect." The fact that demand fell in supply-inelastic areas, and rose in supply-elastic areas, motivates us to study the long-run effects of regional demand changes on rental affordability.

Throughout, we compare the effects of remote work to a counterfactual where location and housing demand did not change. This means that our estimates are conservative relative to a counterfactual where location demand continued to shift towards inelastic places, as it had done in the previous two decades (Howard and Liebersohn, 2021).

In the later part of the paper, we expand our model to include a notion of house prices as the present discounted value of rents. We find that cross-sectional regressions of short-run house price changes on short-run rent changes give similar coefficients in both the model and the data, lending credibility to the long-run predictions of our model.

The structure of the model allows us to easily calculate the long-run effects of remote work under a variety of possible scenarios: first, we consider alternative assumptions about the effects of remote work on housing demand, and second, we consider different assumptions about the future of remote work. Since the location demand channel scales linearly with the size of the shock, an increase in remote work will raise the location demand channel proportionally to our baseline estimate. Finally, we consider alternate assumptions about how remote work might affect where people decide to move.

1.1 Literature Review

Prior to the COVID-19 pandemic, only a few papers considered the implications of remote work. Blinder (2005) emphasized the potential tradability of service jobs through improved telecommunications. Ozimek (2019) argued that occupational tradability predicted domestic remote work and not job loss. Dingel and Neiman (2020) extended this research by calculating the remote work potential for jobs across cities, introducing occupational remote-ability scores that are widely used today.[4]

The rise of remote work during the pandemic sparked increased research interest, particularly regarding its impact on the housing market. Within cities, remote work shifted housing demand from high-density, high-cost areas to lower-density, lower-cost locations (Davis et al., 2021; Ramani and Bloom, 2021; Gupta, Mittal, Peeters and Van Nieuwerburgh, 2021; Brueckner, Kahn and Lin, 2021). Remote work also shifted housing demand across cities, moving demand from high productivity, high cost, high density places towards lower productivity, lower cost, lower density places (Davis et al., 2021; Ozimek, 2022; Althoff, Eckert, Ganapati and Walsh, 2022; Liu and Su, 2021; Brueckner et al., 2021). Remote work also increased the overall demand for housing in the short-run (Davis et al., 2021; Mondragon and Wieland, 2022; Ozimek and Carlson, 2023).

We build on this research by considering the long-run implications of remote work for aggregate housing costs using a spatial equilibrium model. While existing literature has predominantly focused on cross-sectional demand changes during the pandemic, our contribution lies in studying the aggregate long-term effects of remote work on housing affordability. To understand these implications, we propose a model of the aggregate housing market that incorporates the interaction of local markets through migration.[5] Our results show that the effects of remote work can be quite different in the long run as compared to the short run.

Another line of research uses quantitative spatial equilibrium models to investigate remote work. These models incorporate rich features such as spatial spillovers and a model of production. In contrast, our more-parsimonious model highlights the particular mechanism we have in mind and allows us to solve for sufficient statistics related to those mechanisms. Davis et al. (2021) examine the productivity effects of remote work and highlight adoption externalities that contribute to its rapid increase. Although their model considers short-run inelastic housing supply and long-run supply adjustment, their focus lies in productivity

[4] Alongside this, a large literature estimates the share of jobs that are done remotely, including Barrero, Bloom and Davis (2020); Mertens, Blandin and Bick (2022); Brynjolfsson, Horton, Ozimek, Rock, Sharma and TuYe (2020); Ozimek (2020); Bartik, Cullen, Glaeser, Luca and Stanton (2020); Mongey, Pilossoph and Weinberg (2021).

[5] Schubert (2022) studies similar spillovers across housing markets through migration but does not focus on remote work.

and income implications rather than affordability. Their long-run counterfactual assumes an infinite elasticity of housing supply, while our study assumes finite and empirically-grounded housing supply elasticities, which are crucial when analyzing long-term rent effects.

Delventhal and Parkhomenko (2020) and Delventhal, Kwon and Parkhomenko (2022) estimate the welfare, price and mobility effects of the rise of work. Both papers feature endogenous agglomeration externalities and congestion costs, and Delventhal and Parkhomenko (2020) models the underlying reasons for increased remote work, distinguishing technological from preference-based reasons. Both papers are focused on the long-run, but they find one similar result to ours, which could be interpreted as a difference between the short- and long-run: when floor space is not allowed to adjust to the remote work shock in their model, residential rents are higher.[6] Given the focus of their paper on the reasons for greater remote work and the impressive quantitative features that shed light on its implications for income and welfare, it is not possible to decompose this exercise into a location demand or housing demand channels as we do here.

2 Data

We create a panel of migration, real rents, house prices, and other covariates at the county level. We use county-level data because we want to capture changes in demand in relatively narrow areas: for example, we hope to measure differences between suburbs and center cities. We face a tradeoff between granular geographic and data coverage because geographic units narrower than counties tend to have sparse data coverage. For example, ZIP code-level rent data does not cover the entire country, and imputing it from higher geographic levels would lead to inaccuracy. We chose counties as the constrained-best mix of narrow geographies and data availability.

In Howard and Liebersohn (2021), we use long-run housing supply elasticity from Saiz (2010); however, the Saiz (2010) elasticities are disadvantaged in that they only include MSAs and miss rich geographic variation within MSAs. Instead, we use the census tract-level elasticities in Baum-Snow and Han (2022), which we aggregate to the county level by taking the population-weighted average across tracts.[7] We use their preferred measure, the quadratic finite-mixture-model elasticities of housing square footage.

The elasticities in Baum-Snow and Han (2022) are only available in certain areas, meaning

[6]Comparing columns 2 and 5 of Appendix Table G.1 of Delventhal and Parkhomenko (2020), allowing floor space adjustment causes a 17% relative decline in rents.

[7]Importantly, the Baum-Snow and Han (2022) elasticities are estimated using a ten-year interval, which may not correspond to the long-run. In section 4.2, we discuss how we adjust the estimates to correspond to the long-run in section 4.2.

that some rural areas are missing from the elasticity measure. Our model requires elasticities for the entire country, so we impute them by assuming that they are equal to the 95th percentile of elasticity in the data, which is about one. Housing supply elasticity is closely related to population density, and this value is roughly what we would expect based on the population density of rural areas in the data. Appendix Figure A1 shows that the missing locations are at roughly the 5th percentile of population density.[8]

In the cross-section, movements in rents and house prices during this time are highly correlated.We focus on rents for the quantitative exercises, so as not to worry about changes in interest rates or expectations that may have affected home prices. At the same time, we believe our results can be useful for thinking about house prices in the long-run.

Data on both prices and rents comes from Zillow: for prices, we use the Zillow Home Value Index (ZHVI) at the county level, and for rents, we use the Zillow Observed Rent Index (ZORI) which is provided to us by Zillow at the county level. The ZORI is the average of the middle quintile of rents in each location, created using a repeat-sales methodology similar to Ambrose, Coulson and Yoshida (2015). It is then reweighted to be representative of the entire housing market with weights calculated using property characteristics from the American Housing Survey. Finally, it is seasonally adjusted and smoothed using a three-month moving average.[9]

The ZORI has several advantages over other rent indexes. One advantage is that it is representative of the *entire* housing market, not just the multifamily market like data from CoreLogic and other sources. Compared to CPI-rents it is available at a more granular level and for a larger number of locations, and it is more high-frequency and less smoothed. We do expect the ZORI to closely match CPI-rents over long-time horizons when we consider the locations used to calculate CPI. To understand the implications of our results for CPI, we will consider the effect on those locations explicitly.

The ZORI includes rents for areas that include most of the U.S. population but it is still missing for many rural places; we infer what is happening in these places using price data. To extrapolate rents for these locations, we run a cross-sectional regression of rent changes on price changes and take the fitted values wherever the ZORI is missing. Appendix Figure A2 shows rent changes and inferred rent changes for places with and without ZORI data. In general, places with missing rents data tend to have low population, and since our results are population-weighted, this procedure is unlikely to matter that much.

[8]Importantly, alternative assumptions about the housing supply elasticity of missing areas have almost no effect on the overall estimates because implied rent changes in these areas are close to the national average. Therefore the covariance of elasticity and rent changes, which we show is a central statistic, is not affected much by alternative assumptions.

[9]For more detail, see https://www.zillow.com/research/methodology-zori-repeat-rent-27092/ .

Population changes come from Census and post office change of address requests. The post office data is the result of a Freedom of Information Act request from Ramani and Bloom (2021), and we clean the data in the same way as Ramani and Bloom (2021). Specifically, we measure gross address changes in each ZIP code as the gross number of individual moves plus the gross number of households multiplied by 2.5. Net moves are the difference between gross moves in and gross moves out. We aggregate moves at the ZIP level to the county level using a correspondence file from the Missouri Census Data Center. Finally, we adjust the population growth rate in all regions by a constant, to reflect the fact that the post office changes capture more outmigration than inmigration, and that the overall population grew slightly during this time period. We pick the constant to match the aggregate population growth as estimated by the Census Bureau.

We validate the use of the post office data by comparing it to a sub-time-period in which we can compare it to estimates from the U.S. Census. We do this in Appendix B.

Data on remote work comes from Kolko (2020). This measure builds on the work-from-home propensity measure developed by Dingel and Neiman (2020) and is aggregated to the county level using employment shares from U.S. census data.

We measure natural amenities using the natural amenities scale from the United States Department of Agriculture Economic Research Service (2019). The scale combines six climate, topography, and water measures and is available at the county level. The highest-amenity places are coastal areas with warm winters, and the lowest-amenity places are flat, landlocked locations with extreme weather.

All nominal variables are deflated by CPI.

3 Stylized Facts

This section reviews stylized facts about the time series and cross-section of the U.S. housing market from 2020 to 2022. These facts are the main aggregate and regional patterns that our model is intended to interpret. They will also be a natural benchmark for comparison to the long-run changes we discuss in Section 6.

3.1 Rent and Population Changes

The first fact we document is the increase in real housing costs coinciding with the rise of remote work. Figure 1 shows real rents and real house prices indexed to January 2020. Real rents rose by about eight percentage points, with most of the change concentrated in early 2021. Real house prices rose by about twenty-five percentage points. The fact that rents and house prices rose at about the same time suggests a role for an underlying shock affecting both markets.

Based on the timing of rent and price changes, we think that changes during the COVID-19 pandemic increased demand for housing. Possible reasons include both rising demand for space due to remote work and an increased rate of household formation. We think that remote work increases demand for home offices (Behrens, Kichko and Thisse, 2021; Stanton and Tiwari, 2021) and raises the value of living space if people spend more time there. For these reasons, we think that remote work played an important role in raising housing demand.

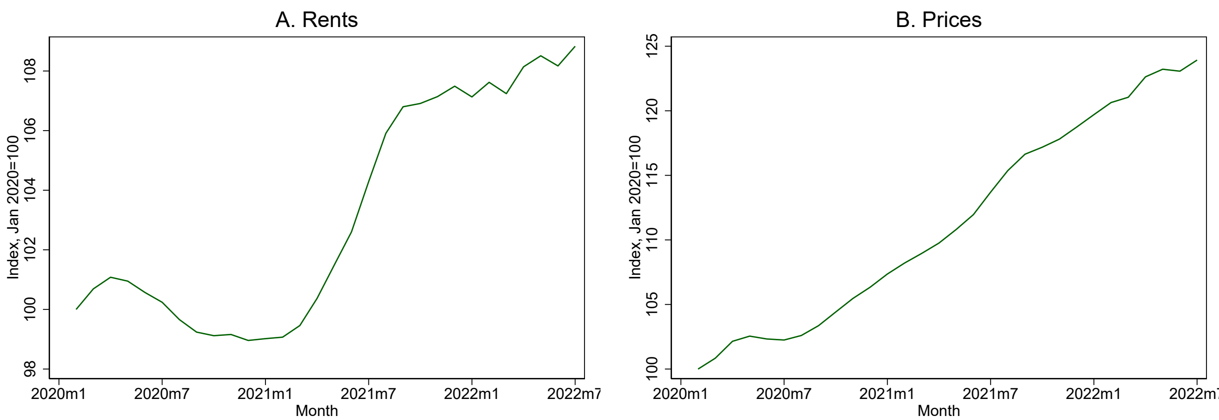
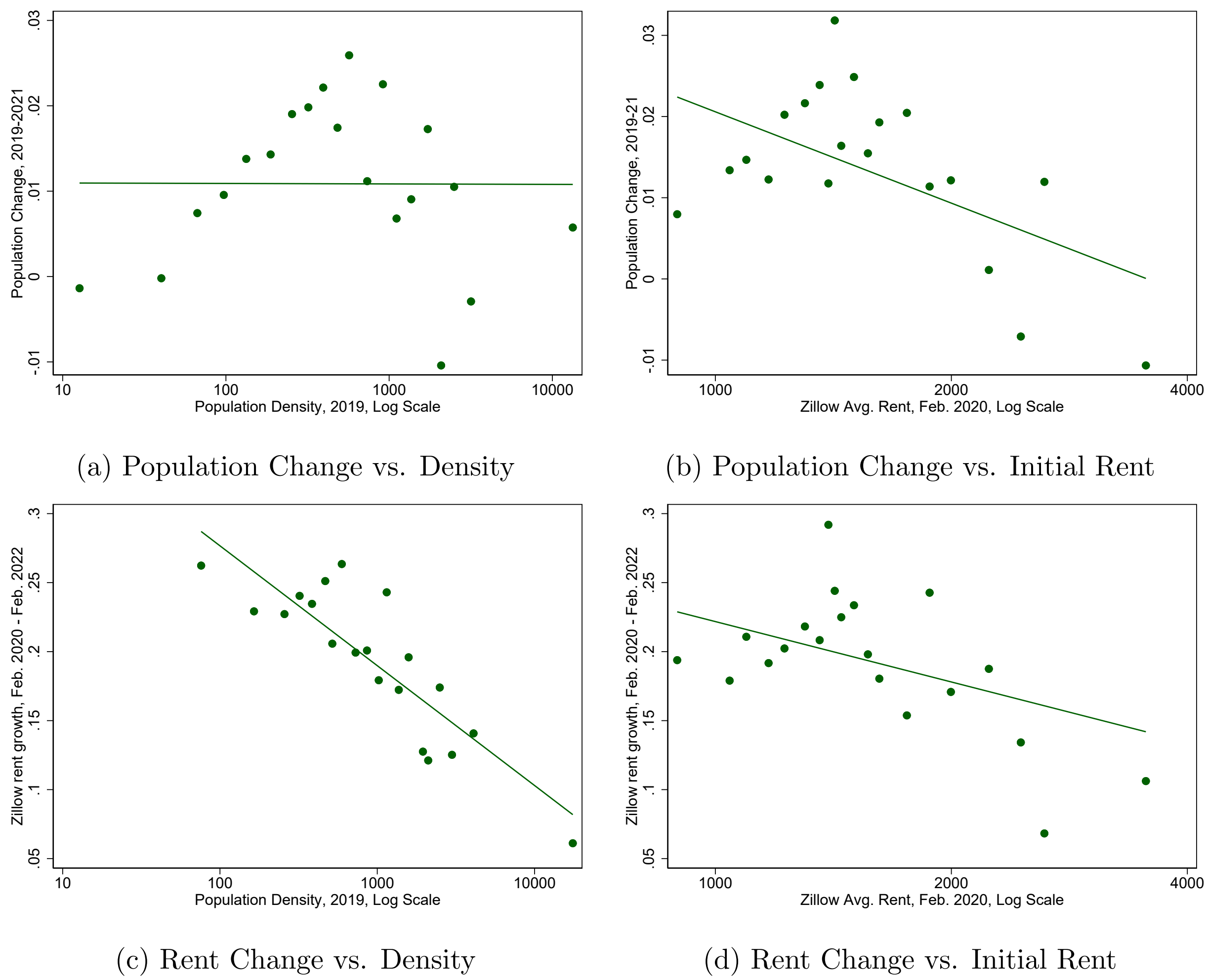


Figure 1: Panel A of shows the ZORI (Zillow Observed Rent Index) indexed to January 2020 dollars. Panel B shows the ZHVI (Zillow Home Value Index) indexed to January 2020 dollars.

The second fact we document is changes in where people demanded housing. Demand shifted away from high-density, high price areas (like city centers) and towards lower-density, lower price areas, such as suburbs and rural areas. Figure 2 provides evidence using price and population data. Panel (a) is a binned scatter plot of county-level population changes from 2019 to 2021 against county population density. Panel (b) is a binned scatter plot of county-level real rent changes against population density. Panels (c) and (d) show population and rent changes respectively graphed against average rent levels from Zillow.[10]

Panels (a) and (b) provide evidence that housing demand shifted from dense central business districts (CBDs) to relatively suburban and rural areas. These figures are consistent

[10] We use binned scatter plots repeatedly through the paper to show data, since showing every county is too dense to read easily. A binned scatter plot sorts the data by the x-variable, and then splits them into an even number of bins. For each bin, it plots the mean of the x-variable against the mean of the y-variable. It is good for showing the conditional average value of the y-variable, given the x-variable, but does not give a sense of the variance of the y-variable.



(a) Population Change vs. Density

(b) Population Change vs. Initial Rent

(c) Rent Change vs. Density

(d) Rent Change vs. Initial Rent

Figure 2: This figure shows binned scatter plots. Panels show the relationship between rent/population changes and population density (Panels A and B) and between rent/population changes and ex ante prices (Panels C and D). Plot created with 20 bins, which are weighted by 2019 county population.

with the evidence in several recent papers showing shifting demand away from city-centers.[11] Population changes are U-shaped; populations fell the most in the densest and most expensive counties, but rose the most in areas with densities and rents near the middle of the distribution. This confirms the "donut" pattern documented in Ramani and Bloom (2021). As with the time series rise in rents, we might expect changes to housing demand to come either from the rise in remote work or from temporary pandemic-related factors. We find no evidence for a reversal in the location of housing demand, suggesting that temporary pandemic factors were not the main driver.

[11] Papers documenting similar changes in the demand for density due to remote work include Delventhal et al. (2022), Liu and Su (2021), Gupta et al. (2021), Brueckner et al. (2021), Rosenthal, Strange and Urrego (2022), and Ramani and Bloom (2021).

Panels (c) and (d) of Figure 2 show that the relative rise in demand for low-density areas also led to a rise in demand for cheaper areas. Rents rose by less in the highest-price, most dense areas. Rent data is not available in the lowest-density areas so the U-shaped pattern is not as pronounced in panels (c) and (d). The association between demand for low density and low-cost areas is not surprising, because rural areas tend to have lower rents. If living near a central city is no longer desirable, the places people move to will be cheaper. In addition, if remote work increases demand for space, we would expect them to move to areas where space is cheaper. What is more surprising is that rents rose even in places where they were cheap pre-pandemic (these places also have a high housing supply elasticity).

3.2 Discussion

The time series and cross-sectional changes shown in Figures 1 and 2 point to changes in housing demand during the pandemic. The patterns in these figures motivate a model which can capture different types of demand shocks coming from the rise of remote work: first, a shock to demand for location (i.e., location outside city center), and second, a shock to housing demand, since people want bigger houses or want to form new households.

Previous papers have already documented many of the same facts, such as the shift in demand from central cities to lower-density suburban areas. Our goal is to interpret changes in rents and populations through a structural model that allows us to make predictions for the long-run effects of housing supply elasticity. To model these shocks, we build on the long-run housing market model developed in Howard and Liebersohn (2021).

The model in Howard and Liebersohn (2021) interprets changes in rents, populations, and housing quantities using housing demand shocks, location demand shocks, and housing supply shocks. To capture the short-run dynamics of the housing market from 2020-2022, we modify this model by setting the housing supply elasticity to zero in the short run. Assuming that housing supply is inelastic in the short run captures a key fact of the pandemic: housing prices rose everywhere, even in places where it used to be very easy to build. We think that inelastic short-run housing supply is a good approximation because the rise in rents—even in rural areas—suggests that the housing supply could not accommodate demand changes right away. Permitting can take years even in relatively flexible housing markets, and evidence from Glaeser and Gyourko (2006) shows that the construction sector generally responds to demand shocks with long lags. Supply chain disruptions during the pandemic may also have made construction delays worse than otherwise.

The first step in our analysis is to back out the shocks to location and housing demand using the structure of our model. The result is a location-specific housing demand and location demand shock implied by changes in rents and populations. In the long run, we think that housing supply is somewhat elastic. To simulate the long-run effects of remote work, we consider the same shocks in a model where supply elasticities are their pre-pandemic long-run values. With the same location and housing demand shocks in the long-run version of model, we can calculate the net effects on real rents.

One approach taken in the literature has been to run reduced-form regressions of changes in housing costs (or population) on regional characteristics. Reduced-form regressions are insufficient if we want to make counterfactual statements or understand the long-run effects of new construction. One reason is that the long-run depends differently on the different demand shocks which reduced-form estimates cannot distinguish. For example, remote work increases the demand for housing and lowers the attractiveness of living in the CBD of major metros. Both of these forces will cause people to move to more rural areas where housing costs are lower. In the long run, this movement will decrease rents because housing is more elastic in cheaper, more rural areas. In addition, rents will fall as supply is able to respond since supply everywhere is more elastic in the long- than the short-run.

We abstract away from the ultimate sources of location and housing demand shocks, some of which have been considered in the previous literature (Davis et al., 2021; Delventhal and Parkhomenko, 2020). The approach allows for a model that is rich enough to capture the key housing market changes that occurred during the pandemic, while also providing intuitive formulas for the long-run effects of remote work that we can derive analytically. At the same time, the model is flexible enough to discuss how results might be different under different assumptions about the future of remote work, or with different assumptions about the elasticity of housing demand.

4 Model and Calibration

In this section, we modify the model from Howard and Liebersohn (2021) to include both a short- and a long-run component. The short-run version of the model assumes the housing supply is inelastic everywhere whereas the long-run version allows for location-specific housing supply elasticities. We show how to use the short-run model to decompose the data into "shocks" to housing demand and location demand, assuming that the housing supply elasticity is zero everywhere. Then, using the long-run version of the model, we derive formulas for the effect of the shocks on housing costs in the long-run.

This section lays out the framework to tell us how to interpret the short-run data and calculate the long-run equilibrium effects. In later sections, we will use this framework, along with observed data from 2020-2022, to estimate the long-run effects of the housing market shocks of recent years.

4.1 Model

We consider a model of I discrete locations, indexed by i, over three time periods, $T = 0, 1, 2$, where $T = 0$ is the pre-pandemic period, roughly early 2020, $T = 1$ is the short-run, roughly early 2022, and $T = 2$ is the long-run. A mass L of people, indexed by j, choose a location and a housing quantity at time $T = 0$. Housing is produced and supplied according to a long-run housing supply curve. A fraction of people adjust their location and housing quantity at $T = 1$, but the quantity of housing is held fixed. In the long-run at $T = 2$, everyone adjusts and housing is built along the original housing supply curve. For most of our analysis, we consider the log-differences between $T = 0$ and $T = 1$, which we call short-run changes, or $T = 0$ and $T = 2$, which we think of as long-run changes. We typically suppress the T notation for simplicity.

Individuals choose location based on a location specific utility—which incorporates wages and amenities—and the rent. They also receive a match-specific utility shock, which we assume is distributed as an i.i.d. Gumbel as is standard in the literature.[12]

$$U_{ij} = v(u_i, r_i) + \zeta_{ij}$$

where u_i is a city-specific term that accounts for wages and amenities, and r_i is the rent. $v(\cdot, \cdot)$ is decreasing in r_i, and we assume that its elasticity is -1.[13]

Per-capita housing demand is then given by

$$h_i = h(x_i, r_i) \tag{1}$$

where x_i is a housing demand shifter, such as wages or the demand for remote workspace.[14] We assume $h(\cdot, \cdot)$ is decreasing in r_i with a constant elasticity λ.

In periods $T = 0$ and $T = 2$, housing production is described by $H_i = Z_i^{\frac{1}{\sigma_i+1}} X_i^{\frac{\sigma_i}{\sigma_i+1}}$, where Z_i is local land and X_i is the tradable good whose price is normalized to one. This defines

[12] Howard and Liebersohn (2021) shows how to think about wages and amenities directly, but we bypass that for simplicity. As an example, if utility were Cobb-Douglas over housing consumption with housing share α and had an additive amenity term a_i, then $\log v(u_i, r_i) = u_i - \alpha \log r_i$, where $u_i = \log w_i + a_i$.

[13] The real assumption is that the elasticity is constant. Once we have made that assumption, choosing -1 is a normalization.

[14] Howard and Liebersohn (2021) discusses x_i as a function of wages, and other housing demand shifters, but we use x_i as a summary measure for simplicity. For example, if housing demand were Cobb-Douglas with housing share α, then $h_i = x_i/r_i$, where $x_i = \alpha w_i$

a supply curve:

$$\log H_i = \sigma_i \log r_i + \text{constant}_i \tag{2}$$

Crucially, housing supply elasticity depends on i.[15]

Local housing markets clear, so the total amount of housing is the per capita housing times the population.

$$H_i = L_i h_i \tag{3}$$

Everyone must live in a city:

$$L = \sum_i L_i \tag{4}$$

where L is the total population of the country.

Because of the extreme value distribution, the population of a city at time $T = 0$ or time $T = 2$ is:

$$L_i = L \frac{v(u_i, r_i)^\mu}{\sum_k v(u_k, r_k)^\mu}$$

where $1/\mu$ is the scale parameter of the Gumbel distribution. The summation in the denominator is over all cities in the economy. Taking the log of the previous equation,

$$\log L_i = \mu \log v(u_i, r_i) - \tilde{u} \tag{5}$$

where $\tilde{u}$ is defined as $\log \sum_k v(u_k, r_k)^\mu$. Importantly $\tilde{u}$ is an endogenous object, but it does not depend on i.

Equations (1)-(5) define the equilibrium at time $T = 0$. For time $T = 1$ and $T = 2$, we consider deviations from that equilibrium.

First consider $T = 2$, i.e. the long run. We take a log-linearized approximation of the indirect utility around the steady-state, as in Howard and Liebersohn (2021):

[15]We assume that housing supplies are exogenous and fixed. We check to see if endogenizing the housing supply elasticities matters for our quantitative results in Appendix E. In particular, we allow elasticities to decrease as housing demand increases, in line with the negative cross-sectional relationship between rents and elasticities. The difference in results is numerically negligible.

$$d \log h_i = -\lambda d \log r_i + \epsilon_i \tag{6}$$

$$d \log H_i = \sigma_i d \log r_i + \xi_i \tag{7}$$

$$d \log L_i = -\mu d \log r_i + \eta_i - d\tilde{u} \tag{8}$$

$$d \log H_i = d \log L_i + d \log h_i \tag{9}$$

$$d \log L = \sum_i L_i d \log L_i = \mathbb{E} d \log L_i \tag{10}$$

where the expectation is initial-population-weighted. η_i is a shock in location demand, ϵ_i is a shock to housing demand, and ξ_i is a local shock to housing supply. λ is the housing demand elasticity and μ is the location demand elasticity.[16] We assume both elasticities are constant across cities. These five equations are a housing demand (per capita) curve, a housing supply curve, a location demand curve, a housing market clearing condition, and a population adding-up constraint. Note that the adding-up constraint is a log-linear approximation.[17]

With these equations, then for any set of shocks ϵ_i, η_i, and ζ_i, we can calculate the log change in rents, housing quantities, and populations.

The short-term, $T = 1$, has a similar structure, but with a couple of key differences. We assume that short-term housing supply is fixed, and we allow only a fraction ϕ of people to adjust the size or quantity of their housing in response to the shocks.[18] The $1 - \phi$ fraction of people that cannot adjust stay in the same location and consume the same amount of housing as they did at $T = 0$. The housing market clearing condition, and the population

[16] For the elasticity with respect to $v(\cdot, \cdot)$ to be μ (as in equation (5)) and the elasticity with respect to r_i to be $-\mu$ (as in equation (8)), we make the assumption that the elasticity of utility with respect to rent is -1. This saves us a bit on notation.

[17] While there is error induced by the log-linear approximation, it is approximately half of the variance of population changes in the counterfactuals, and empirically, it is quite small.

[18] Even though ϕ plays a similar role to λ and μ in the short-run, it does not appear in the equations governing the long-run, so in effect, it is governing how different the endogenous response of people can be in terms of how much they move.

adding-up constraint are the same as in the long-run. The equations for $T = 1$ are:

$$\frac{1}{\phi} d\log h_i = -\lambda d\log r_i + \epsilon_i \tag{11}$$

$$d\log H_i = 0 \tag{12}$$

$$\frac{1}{\phi} d\log L_i = -\mu d\log r_i + \eta_i - d\tilde{u} \tag{13}$$

$$d\log H_i = d\log L_i + d\log h_i \tag{14}$$

$$d\log L = \sum_i L_i d\log L_i = \mathbb{E} d\log L_i \tag{15}$$

In contrast to the long-run equations, we will use these equations, along with data on population changes and rent changes to infer what the shocks ϵ_i and $\eta_i - d\tilde{u}$ are in the short-run. We go into more detail in the following subsections.

4.1.1 Calculating shocks from the short-run model

Using equations (11)- (14), we can use the short-run model to identify the shocks to housing demand and location demand (up to a constant):

$$\epsilon_i = -\frac{1}{\phi} d\log L_i + \lambda d\log r_i \tag{16}$$

$$\eta_i = \frac{1}{\phi} d\log L_i + \mu d\log r_i + d\tilde{u} \tag{17}$$

This is done by solving the system of linear equations for ϵ_i and η_i, so that it can be expressed in terms of observed moments of the data: the change in population and rents.

4.1.2 Long-run effect of housing demand shocks

If those same shocks persist into the long-run, we can estimate their effect on the long-run rents using a version of the model where the σ_is are set to their long-run values. Define the Housing Demand Channel to be the difference in average rents at $T = 2$, $\mathbb{E} d\log r_i$, between an equilibrium with the ϵ_i shocks and an equilibrium where the ϵ_i shocks are all set to 0.[19]

[19] The algebraic derivation for equation (18) can be found in Howard and Liebersohn (2021). It is an algebraic rearrangement of equations (6)-(10).

Then, for the housing demand shocks ϵ, their long-run effect on aggregate rents is:

$$\text{Housing Demand Channel} = \frac{\mathbb{E}\frac{\epsilon_i}{\lambda+\mu+\sigma_i}}{\mathbb{E}\frac{\lambda+\sigma_i}{\lambda+\mu+\sigma_i}} \tag{18}$$

$$= -\frac{1}{\phi}\frac{\mathbb{E}\frac{d\log L_i}{\lambda+\mu+\sigma_i}}{\mathbb{E}\frac{\lambda+\sigma_i}{\lambda+\mu+\sigma_i}} + \lambda\frac{\mathbb{E}\frac{d\log r_i}{\lambda+\mu+\sigma_i}}{\mathbb{E}\frac{\lambda+\sigma_i}{\lambda+\mu+\sigma_i}} \tag{19}$$

where equation (19) comes from plugging equation (16) into equation (18). Note that if $\mu = 0$, then (18) simplifies to $\mathbb{E}[\epsilon_i/(\lambda+\sigma_i)]$, and if $\mu \to \infty$, then (18) simplifies to $\mathbb{E}[\epsilon_i]/(\lambda+\bar{\sigma})$ where $\bar{\sigma}$ is the average of σ_i, weighted by population.

Intuitively, the housing demand channel is larger when the shocks to housing demand, ϵ's, are larger and smaller when housing demand or supply is more elastic. This effect does not depend on how mobile people are across locations if the demand shocks are uncorrelated to the housing supply elasticities. To note, if population growth is zero and $\mu \to \infty$, then the long-run effect of housing demand is the initial rent increase times $\frac{\lambda}{\lambda+\bar{\sigma}}$. This is the ratio of the sum of the supply and demand elasticities in the short- and long-run, which often shows up in applications of the Le Chatelier (1884) principle.

Similarly, define the Location Demand Channel to be the change in $T = 2$ rents for a particular set of η_i shocks as compared to all the η_i shocks being set to 0.[20] This is given by:

$$\text{Location Demand Channel} = \frac{1}{\mathbb{E}\frac{\lambda+\sigma_i}{\lambda+\mu+\sigma_i}} Cov\left(\frac{1}{\mu+\lambda+\sigma_i}, \eta_i\right) \tag{20}$$

$$= \frac{1}{\phi}\frac{1}{\mathbb{E}\frac{\lambda+\sigma_i}{\lambda+\mu+\sigma_i}} Cov\left(\frac{1}{\mu+\lambda+\sigma_i}, d\log L_i\right) - \frac{1}{\mathbb{E}\frac{\lambda+\sigma_i}{\lambda+\mu+\sigma_i}} Cov\left(\frac{\lambda+\sigma_i}{\mu+\lambda+\sigma_i}, d\log r_i\right) \tag{21}$$

The location demand channel depends on the covariance of the location demand shocks with an expression that depends on the local housing supply elasticity.[21] If the location demand shocks are larger in places with higher elasticities, that will have a negative effect on average rents.

Note that as $\mu \to \infty$, equation (21) simplifies to $-Cov(\sigma_i, d\log r_i)/(\bar{\sigma}+\lambda)$. And if $\mu = 0$,

[20] As with the Housing Demand Channel, the algebraic derivation for equation (20) can be found in Howard and Liebersohn (2021). It is again an algebraic rearrangement of equations (6)-(10). Equation (21) comes from plugging equation (17) into equation (20).

[21] In the short run, the housing supply is zero everywhere, so there can be no net movement to places with a more elastic housing supply. This means that the location demand channel is zero on average. This is apparent in Equation (20) because when we plug in a zero for σ_i everywhere, the covariance is zero, and the location demand channel evaluates to zero.

then the location demand channel simplifies to $Cov((\lambda + \sigma_i)^{-1}, d \log L_i)/\phi$. This is because when μ is large, the location demand shocks are reflected in the rent changes of a place, whereas when μ is small, the population changes are the primary way to measure location demand shocks. In either case, if people want to move to more housing-supply-elastic places, that causes overall housing costs to fall.

4.2 Calibration of Model Parameters

In the next section we will use the formulas from the model to back out the location demand shocks η_i and housing demand shocks ϵ_i. The formulas used to calculate the shocks depend on housing demand elasticities. Here, we discuss the sources of these and other parameters, their interpretation, and the range of estimates that we think are reasonable.

4.2.1 Location demand elasticity μ

The parameter μ governs how sensitive people are to the price in a particular location. A large value of μ decreases agents' location-specific preference and results in a more elastic location demand. At one extreme, $\mu = 0$ would imply that households' location demand is perfectly price inelastic. In this scenario, changes to location demand are reflected in population changes only. At the other extreme, $\mu \to \infty$ implies that households are perfectly elastic to price changes. Previous papers in the tradition of Rosen (1979) and Roback (1982) make this assumption implicitly by equalizing utility across space. When $\mu \to \infty$, shocks to location demand are reflected in the cross-section of real rent changes.

The literature proposes a variety of values for μ, nearly all above one and many as high as infinity.[22] We use $\mu = 1.07$, following Hsieh and Moretti (2019) and Parkhomenko (2020).[23] We will show that ultimately the estimates depend very little on the particular value of μ that we choose for the calibration.

4.2.2 Housing demand elasticity λ

The housing demand elasticity tells us how much housing demand declines as a function of housing costs. At one extreme of the literature, $\lambda = 1$ corresponds to Cobb-Douglas demand, so households spend a constant portion of their income on housing in each city, regardless

[22]See Table 1 of Howard and Liebersohn (2021) for a review of different values of μ and λ. Fajgelbaum, Morales, Suárez Serrato and Zidar (2019) Table A.17 also provides estimates of a related elasticity: the elasticity of labor supply with respect to wages, for which our calibration of μ is roughly consistent.

[23]Hsieh and Moretti (2019) use a population elasticity to wage 1/0.3 and a consumption share of housing of 0.32 in a Cobb-Douglas framework. This implies a population elasticity to rent that is the product of the two. Parkhomenko (2020) uses the same calibration as Hsieh and Moretti (2019).

of the price. At the other extreme, $\lambda = 0$ would imply unit housing demand, so housing quantities do not change with price.

We use $\lambda = \frac{2}{3}$ as our benchmark value, based on an estimate from Albouy, Ehrlich and Liu (2016). We discuss how important the value of λ is in this setting in Section 6.2.

4.2.3 Mobile share of households ϕ

The parameter ϕ governs the fraction of households that are allowed to adjust their housing in the short run. If $\phi = 1$, all households adjust their housing and location based on their demand shocks and the rent changes. If ϕ is small, the model will interpret the same data as coming from a larger underlying shock but where fewer households are allowed to move. In this case, the long-run effects of the shock may be larger than the short-run.

We think ϕ is the hardest parameter to calibrate because there is little evidence about it. We view different values of ϕ as making different predictions about the future of remote work. Ozimek (2022) provides survey evidence from November 2021 that four times as many households plan to move because of remote work as were able to. If all these households end up switching to working remotely and that none did between November and February, it will imply that $\phi = \frac{1}{4}$. Therefore, as our benchmark we take $\phi = \frac{1}{2}$, which we consider conservative relative to the survey results. We also consider other values of ϕ as a way to explore the range of possible effects that remote work might have. Overall, we think that ϕ between $\frac{1}{4}$ and 1 may be possible.[24]

4.2.4 Housing Supply Elasticities σ_i

The parameter σ_i, which varies by location, governs the long-run housing supply elasticities of each individual county. As discussed in Section 2, we base our calibration on Baum-Snow and Han (2022), which estimates 10-year elasticities at the Census-tract level. We aggregate them up to county-level by taking the average elasticity within a county, weighted by the quantity of housing.

However, for a slowly depreciating asset like housing, 10-year elasticities are not the same as long-run steady-state elasticities, which we require for the model. Consider the following housing production function, in which housing depreciates at rate δ and σ_i governs

[24] An alternative lower-bound for ϕ is the share of people that did move during the time period. About 10 percent of Americans move every year, so a reasonable lower bound might be about 20 percent.

the short-run investment elasticity:[25]

$$H_{it} = (1-\delta)H_{it-1} + Z_i p_{it}^{\sigma_i}$$

where p_{it} is the price of housing, which (in the long-run steady-state of some models) is proportional to rents. In this case, the long-run elasticity of housing supply—the quantity we are interested in—is σ_i. However, what would be measured as a ten-year elasticity is $(1-(1-\delta)^{10})\sigma_i$.[26]

So, for our baseline calibration, we use

$$\sigma_i = \sigma_{\text{Baum-Snow and Han (2022)}} \frac{1}{1-(1-\delta)^{10}}$$

We calibrate $\delta = 0.03636$, based on the depreciation rate in the U.S. tax code, but which is also similar to estimates in Glaeser and Gyourko (2005).[27] Doing the arithmetic, this means we multiply the elasticities from Baum-Snow and Han (2022) by 3.23. However, so that readers can understand the implications of this assumption, we also present our results using the unadjusted Baum-Snow and Han (2022) elasticities throughout the paper, which are qualitatively similar to our main results.

5 Effect of Remote Work on Housing Demand

With the calibrated parameters we could, in principle, use equations (19) and (21) in order to estimate the size of the housing demand channel and the location demand channel without estimating any shocks; however, we think it is helpful to first describe the estimated housing demand shocks, ϵ_i, and the location demand shocks, η_i, and then estimate the magnitudes of the channel to better understand the intuition behind the two channels. We do this in this section.

[25] A similar equation is used in a discrete-time infinite horizon model in Appendix C that nests our simple three-period model, so we can think of this calibration exercise as making the calibration of σ_i consistent with our model.

[26] This formula is a log-linearization. We show the derivation in Appendix C.2.

[27] Glaeser and Gyourko (2005) give different depreciation rates for each decade from 1920 to 2000, ranging from 0.02 to 0.113. However, six out of eight of them are between 0.02 and 0.048. They also estimate depreciation over multiple decades and find lower numbers, ranging from 0.016 to 0.039. Our calibration of 0.03636 is within the range of their values, on the slightly higher end, leading to more conservative estimates of the long-run differences.

5.1 Demand Shock Estimates

Location demand shocks η_i Equation (17) shows that location demand shocks are equal to a linear combination of rent changes and population changes. To estimate the relative location demand shock for a given county, we need data on both the rent change and the population change.

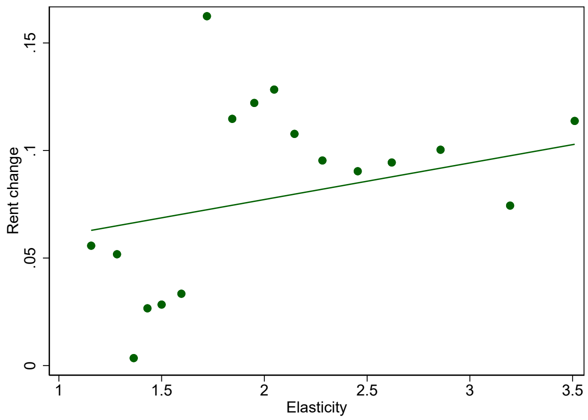
Anticipating the way that we will use them, we know that the important statistic will be the covariance of the location demand shocks with a function of the local housing supply elasticity, and therefore the relationship between rent or population changes and local supply elasticities will matter.

We show a scatter plot plotting the relationship between housing supply elasticity and both rent changes and population changes in Figure 3. Panel (a) of Figure 3 shows the relationship between rent changes and elasticity using a binned scatter plot. Rent increased the least in areas where housing is the most inelastically supplied. For $\mu \to \infty$, local rent changes are equivalent to location demand shocks. For smaller values of μ, population changes matter as well. The relationship between population changes and housing supply elasticity is shown in Panel (b). Again, there is a positive relationship between population changes and housing supply elasticity.

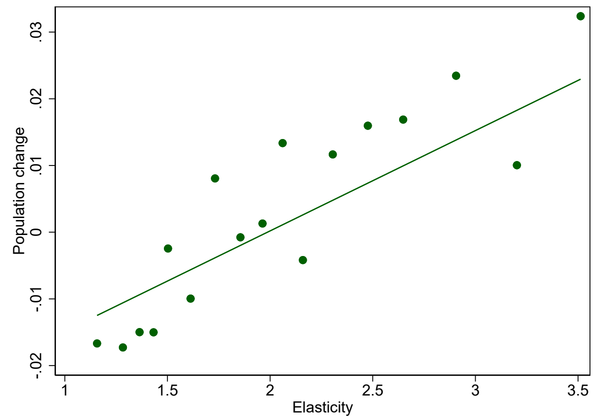
Each location's location demand shock is a linear combination of the rent changes and population changes in Panels (a) and (b). For higher values of μ—the elasticity of population to rents—the location demand shock will be more similar to the rent changes. Importantly, for any parameter combination, location demand is increasing more in areas that are more housing-supply elastic.

Housing demand ϵ_i Like for location demand, housing demand can also be calculated based on observed rent and population changes. Equation (19) tells us that we should care about the average values of the housing demand shocks. This focus is different than location demand shocks, where we anticipated being interested in the cross-sectional variation.

The rise in real rents from February 2020 to February 2022 was about 8 percentage points and U.S. population growth was 0.5 percentage points. Assuming $\lambda = \frac{2}{3}$ and $\phi = \frac{1}{2}$, this implies an average housing demand shock (i.e. ϵ) of .043 (equation 16). This means that in partial equilibrium—i.e. if housing costs had stayed the same—people would have consumed an average of 4.3 percent more housing because of the ϵ shocks.



(a) Rent Change vs. Elasticity



(b) Population Change vs. Elasticity

Figure 3: Binned scatter plot the relationship between real rent changes and housing supply elasticity (Panel A) and between population changes and housing supply elasticity (Panel B). Plot created with 20 bins and weights by 2019 county population. Source: Authors' calculations using data from Zillow and USPS.

5.2 Relation to Remote Work Measures

We now take a brief digression to discuss the relation of the estimates of location demand—the η_i's—to observable measures of remote work. A reader that is impatient to find out the magnitudes of the location demand channel and the housing demand channel may wish to skip to Section 6, and come back to this discussion later.

Up to this point, we estimated the location demand shocks and the housing demand shocks without regard to their origins. Given that one of the major changes in the economy during this time was the rise of remote work, we want to investigate how related the estimated shocks—particularly the location demand shocks—are to remote work variables. One reason to suspect that they are closely related is the findings of previous papers such as Gupta et al. (2021) and Ramani and Bloom (2021). In this section, we show additional evidence that location demand rose in areas we would expect, using proxies for remote work developed in the literature.

Specifically, we show that the η_i's we estimate are located where remote work is possible. To do this, we project the rent and population changes on several observable measures related to remote work, including both vulnerability to remote work in each county itself as well as in nearby counties (to account for spillovers).

Our main measure is the remote work feasibility measure developed by Dingel and Neiman (2020), which calculates the feasibility of remote work by profession. We aggregate it to the county level to measure the remote work vulnerability of each region. Because demand for remote work spills over across counties, we include variables measuring the remote work share in neighboring counties at various distances. We also include measures of relative housing costs because workers tend to move towards relatively cheap areas in their vicinity. Finally, to account for the fact that households moved to areas with nicer amenities, we interact house prices with a natural amenities measure from the USDA.

We project the components of location demand (i.e., population changes and rent changes) onto remote work variables by running the following regression:

$$
\begin{aligned}
y_i = &\beta_1 \mathrm{WFH}_i + \beta_2 a_i + \beta_3 \log(p_i) + \beta_4 a_i \log(p_i) \\
&+ \sum_{\{d\}} [\beta_{5d} \mathrm{WFH}_{id} + \beta_{6d} px_{id} + \beta_{7d} \mathrm{WFH}_{id} px_{id}] + \epsilon_i
\end{aligned}
\tag{22}
$$

where WFH_i is the remote work vulnerability in location i, a_i is the level of amenities, p_i is the house price, and y_i is the population or rent growth from February 2020 to February 2022. We include lower-order terms in addition to interaction terms. For a given distance d, WFH_{id} is the average remote work vulnerability for counties within d miles and px_{id} is the log house price minus the population-weighted average log house price of counties within d miles. To non-parametrically estimate the effects of remote work, we allow the effects to vary at different distances by estimating equation (22) with $d = 25, 50, 100, 250, 500$ miles. The main reason we consider these spatial patterns is because we think people are likely to commute to nearby locations (Monte, Redding and Rossi-Hansberg, 2018). With remote work, those commutes may be less frequent and allow people to live at a fairly large distance to their job.[28]

Estimates show that location demand is very much related to remote work. When we estimate specification (22) using the location demand shock, we calculate an R^2 of 0.37 and an F-statistic of 84.[29] The WFH variation explains less than half of the change location demand, but given the relative coarseness of the measure, we think this is quite high. We also reject at the 1 percent level that the changes are unrelated to WFH.

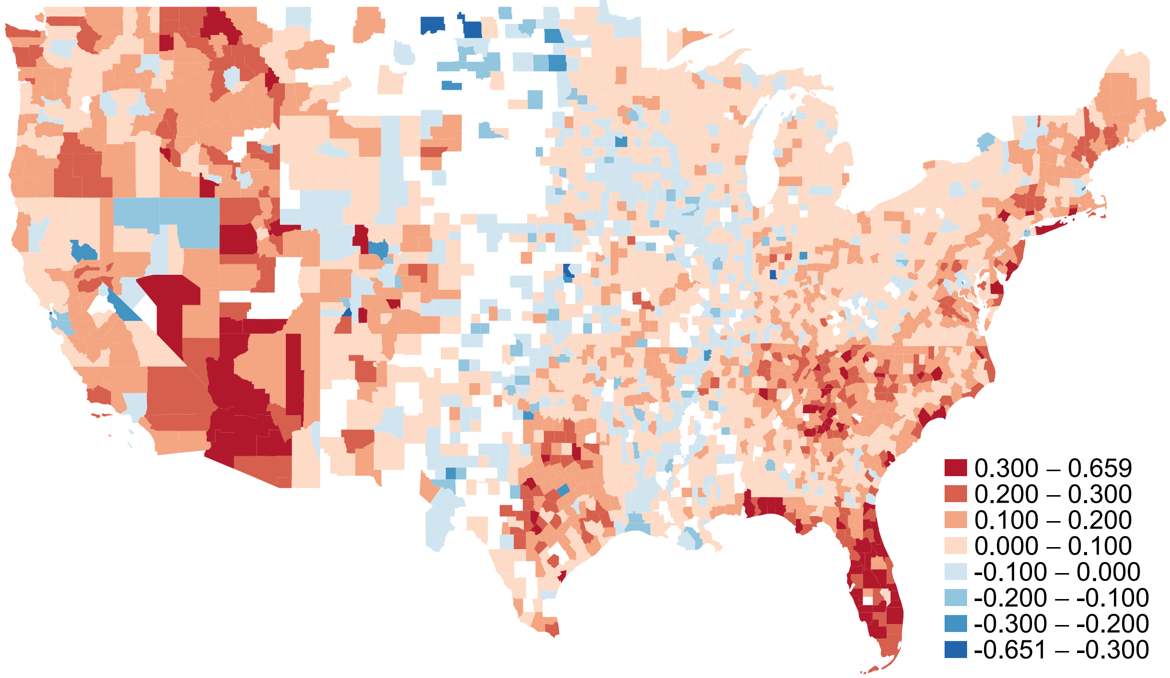
Figure 4 shows that the projection capture a lot of the variation in location demand.[30]The top panel is a map of the United States showing the real rent change at the county level. The bottom panel is a projection of the real rent change onto the remote work shock, estimated in equation (22). The maps look qualitatively very similar, the main difference being that

[28]Another reason distance might matter is thinking about migration (Schubert, 2022).

[29]The coefficients from the regression are available in Table A1. However since we allow the effects to vary at many different distances, many of the x-variables are highly correlated and so the coefficients are not easily interpretable.

[30]Similar maps for rents and population changes are available in Appendix Figures A3 and A4.

A. Location Demand Shocks by County



B. Location Demand Shocks, projected onto Remote Work variables

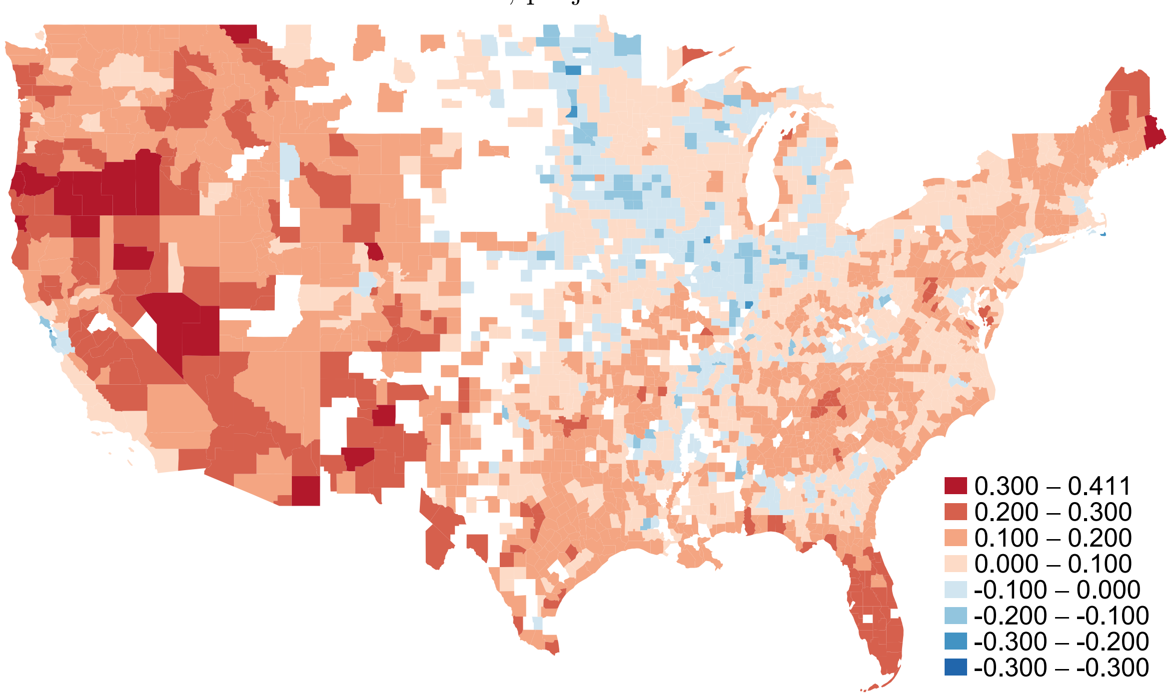


Figure 4: This figure shows location demand shocks and location demand projected onto remote work shocks. Panel A is a choropleth map showing the location demand at the county level. Panel B shows the location demand shock projected onto remote work measures estimated using equation (22). The colors are on the same scale in both maps.

the projection is somewhat smoothed out. This makes sense given that rents are noisy and that our measures will not capture everything that is desirable to remote workers.

Equation (22) is able to capture many of the features that may be associated with remote work. As can be seen in the figure, there are smaller rent predicted rent increases in New York, Los Angeles, and San Francisco, with large increases in the counties surrounding them. There are significant increases in the South, particularly Florida, and in California, which are high amenity regions.

We can do a similar exercise using housing demand shocks to see if remote work variables are highly correlated to that. We run the same regression, but instead use the estimated ϵ's from the model. Under our preferred specification, the R^2 is actually fairly small, around 0.06. More fundamentally, while the projection of location demand shocks are helpful to estimate the long-run effects of remote work, the formulas for the long-run effects of housing demand rely on the average housing demand shock, not the cross-section. This regression does not help us understand the average without stronger assumptions.

6 Long-Run Effects of Remote Work

Having discussed the demand shocks in the previous section, we are now ready to estimate the magnitudes of the housing demand and location demand channels in the long-run.

6.1 Benchmark estimates

Given the location and housing demand shocks from the previous section, we can estimate the location demand channel and the housing demand channel using equations (18) and (20).

These results can be found in Table 1. In our preferred calibration for the entire country (the first row),[31] the long-run location demand channel is -.003 log-points and the long-run housing demand channel is .018 log-points. The total effect is .015 log-points, meaning that the same housing and location demand channels that we measured in the short-run through the lens of our model will increase rents in the long-run by 1.5 percentage points. For comparison, these same effects had a 7 percentage-point impact in the short run, so the long-term impact is only about 20 percent as large as the short-run impact.[32]

[31] Our preferred calibration is $\mu = 1.07$, $\lambda = 2/3$, and the $\sigma_i = 3.23\sigma_{\text{Baum-Snow and Han (2022)}}$.

[32] All of the short-run impact is due to housing demand. The reason there is no location demand channel in the short-run is that all counties have a housing supply elasticity of zero, so there can be no movement to places with differential housing supply. The housing demand channel can change rents in any particular location, but the net effect summed across all locations will be zero.

Table 1: Main Results.

Region	(1) Short Run Total	(2) Short Run Location Demand	(3) Short Run Housing Demand	(4) Long Run Total	(5) Long Run Location Demand	(6) Long Run Housing Demand
			μ=1.07			
National	.07	0	.07	.015	-.003	.018
CPI Cities	.056	-.012	.068	.009	-.01	.018
Expensive Metros	.012	-.06	.072	-.013	-.035	.022
			μ=100			
National	.07	0	.07	.013	-.003	.016
CPI Cities	.056	-.014	.07	-.001	-.017	.016
Expensive Metros	.012	-.058	.07	-.044	-.06	.016
			Baum-Snow & Han Elasticity			
National	.07	0	.07	.037	-.003	.041
CPI Cities	.056	-.012	.068	.025	-.014	.039
Expensive Metros	.012	-.06	.072	-.007	-.05	.043
			Location Demand Projected Onto Remote Work Measure			
National	-	0	-	-	-.001	-
CPI Cities	-	-.007	-	-	-.004	-
Expensive Metros	-	-.057	-	-	-.032	-

Notes: This table shows the main results, as well as alternative calibrations for the model. The numbers represent the percentage point change in rents relative to February 2020. λ is the housing demand elasticity, how much demand for housing demand declines as a function of costs. ϕ is the share of households who want to migrate who are actually able to migrate in the short run. μ is the location demand elasticity, how sensitive people are to prices in each location. The benchmark calibration uses $\lambda = 2/3$ and $\phi = 0.5$. The first two sections show calibrations for μ=1.07 (as in Hsieh and Moretti 2019 and Parkhomenko 2020) and μ=100 (as in Howard and Liebersohn 2021), respectively. The third section shows Baum-Snow and Han (2022) Elasticity with μ=1.07. The fourth section uses a projection of η onto the remote work measure with μ=1.07. CPI cities include all Metropolitan Statistical Areas which are used to calculate CPI. Expensive metros are the counties in the New York, San Francisco, San Diego, Seattle, and Boston Metropolitan Statistical Areas. Within each category, the average is taken by 2019 population.

In the next row, we show the same rent changes but for counties in which CPI is measured, which may be of interest since housing costs make up a large share of the consumption basket in CPI. The short- and long-run housing demand channels are quantitatively similar, but there is a more negative location demand channel in both the short-run and the long-run, as these counties experienced negative location demand shocks compared to the rest of the country. In particular, this brings the long-run total to be less than .01 log-points.

Finally, we also show the same numbers, but for just the five most expensive metropolitan statistical areas in our data: New York, San Francisco, San Diego, Seattle, and Boston. Again, the housing demand channels are comparable to the national average, but the location demand channels are much more negative, meaning the long-run total effect is actually a .013 log-point decrease in rents. Of course, there was a much smaller short-run impact as well, with only a total effect of 0.12 log-points. This highlights the cross-sectional heterogeneity of the impact of remote work, with much different effects on average than in specific high-cost cities.

The model can be solved for long-run rent and population changes in every county. While we show the results for the expensive metros in Table 1, a reader may be interested in other specific areas. For that reason, we have included maps of the cross-section of effects that can be found in Appendix D.

6.2 Alternative Parameterizations

We also present two alternative parameterizations in Table 1 for comparison. In the first, we use a much higher elasticity of population to rents, $\mu = 100$. This approaches the Rosen (1979)-Roback (1982) benchmark of utility equalization everywhere. The results are quantitatively similar for the entire country, with a difference of only .002 log points for the long-run housing demand channel and no different for the long-run location demand channel.

However, when we focus on CPI cities or Expensive Metros, the location demand channel is more negative—almost twice as large. This leads to a long-run total effect on CPI cities of around 0, and a long-run total effect on expensive metros of -0.044 log-points. The reason for this difference is that these areas had the largest negative location demand shocks, so they must be offset by relative rent declines—even in the long-run—when utility is equalized everywhere. When μ is much smaller, as in our benchmark, then people moving into the city, as the housing supply grows, means that the marginal agent can still be indifferent between the two cities with smaller rent adjustments.

The similarity in results for different values of μ is perhaps surprising, given that it does not hold generally, as in Howard and Liebersohn (2021); therefore, it is worth discussing why that is the case. If $\mu \to \infty$, then people are very sensitive to rents, so local rents will adjust to offset location demand changes and the outside option, $d\tilde{u}$. The formula for the location demand channel is given by:

$$\text{Location Demand Channel} = -\frac{Cov(\eta_i, \sigma_i)}{\bar{\sigma} + \lambda} = -\frac{Cov(d \log r_i, \sigma_i)}{\bar{\sigma} + \lambda} \tag{23}$$

On the other hand, if $\mu = 0$, people do not move at all in response to rents, and therefore all movements will be governed simply by the location demand shock. In this case, the formula is given by:

$$\text{Location Demand Channel} = \frac{1}{\phi} Cov\left(\eta_i, \frac{1}{\sigma_i + \lambda}\right) = \frac{1}{\phi} Cov\left(d \log L_i, \frac{1}{\sigma_i + \lambda}\right) \tag{24}$$

In the data, the quantity in equations (23) and (24) are both small in magnitude and negative.[33] Intuitively, this occurs because the patterns of rent changes and population changes are similar in the data. Inelastic places saw a relative decline in rents and in populations. While it is a coincidence that the magnitudes end up being essentially the same regardless of μ, it would be expected that the sign would be negative based on easily observe aspects of the data.

The fact that μ does not greatly affect the housing demand channel is less surprising. The measurement of demand shocks using the short-run data does not depend on μ, and the long-run effects of demand shocks are given by: $\mathbb{E}[\frac{\epsilon_i}{\sigma_i + \lambda}]$ or $\frac{\mathbb{E}\epsilon_i}{\bar{\sigma} + \lambda}$ when μ is 0 or ∞ respectively. These would differ only if the demand shocks and the housing supply elasticity are correlated, and in the data, the demand shocks are positive everywhere, not just in inelastic regions.

Finally, we wish to note that the effect on rents and populations in individual cities are different as we change the calibration of μ. It is only the average effect that is insensitive to its parameterization.

We also show the calibration with lower housing supply elasticities, by using the unadjusted Baum-Snow and Han (2022) elasticities instead of the ones we adjusted for housing depreciation. Mechanically, the short-run results are the same as the benchmark, since the housing supply elasticity does not matter. In the long-run, the location demand effects are comparable, but the housing demand effects are much larger; this is because there was a large increase in housing demand. If supply is constrained to react less, then the price will rise by more. The overall effect is a .037 log-points, which is a bit larger than the baseline estimates, but still much smaller than the short-run effect.

Besides the two alternative calibrations in Table 1, we also show different parameter

[33] For intermediate values of μ, the effect is somewhere in between.

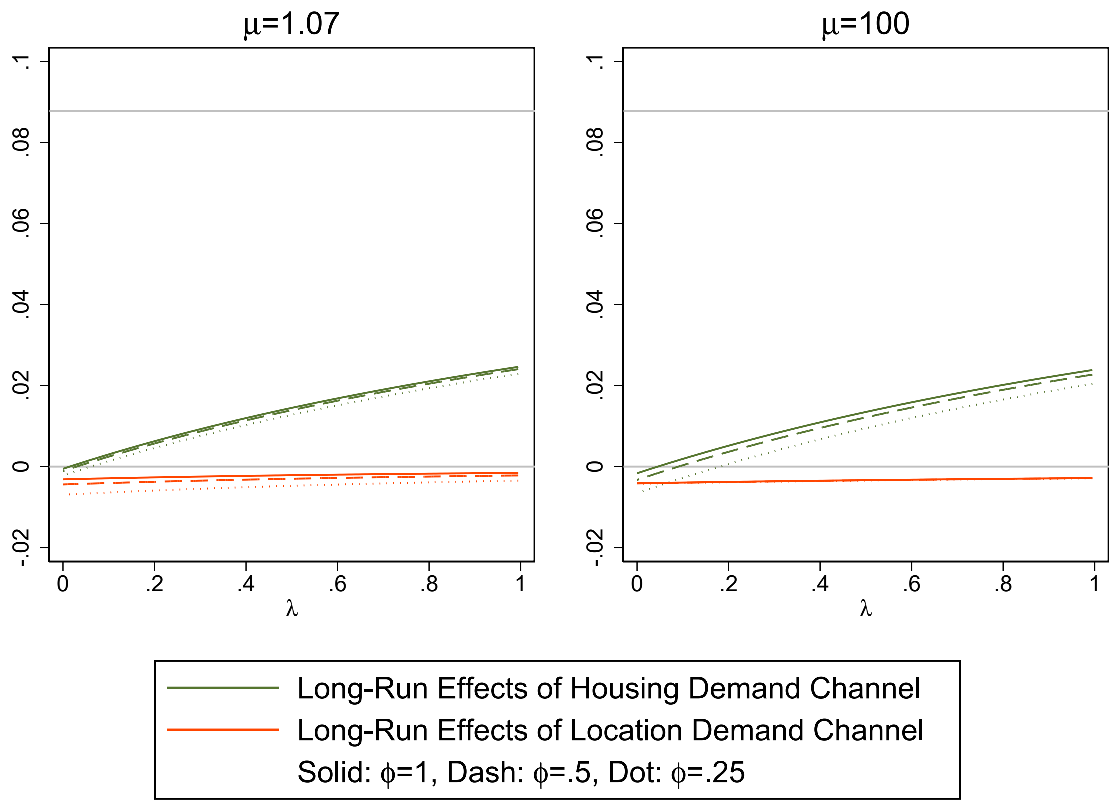


Figure 5: This figure shows the long-run average effects of housing demand and location demand on house prices. The two figures side-by-side consider different and extreme values of the location demand elasticity, μ, with $\mu \to \infty$ representing an extremely high elasticity to move in response to a rent change. λ, on the x-axis is the housing demand elasticity. ϕ, represented by different styles of line within the figure, represents the share of people who adjust their housing and location consumption in the short-run.

combinations of ϕ and λ in Figure 5. We start by reiterating our result regarding μ. Even though there is very little agreement on the population elasticities to rent in the literature, the effects are not very different for extreme values of $\mu = 1.07$ or $\mu \to \infty$ (here we show $\mu = 100$, but this is visually indistinguishable from larger values of μ).

Next, we discuss the sensitivity to λ. When $\lambda = 0$, the size of house that people choose is completely inelastic to rent, and when $\lambda = 1$, then it has unit elasticity. $\lambda = 1$ is the most common parameterization in the literature, but largely due to tractability. When it is estimated as in Albouy et al. (2016), the estimates are usually smaller than 1. Our preferred estimate is $\lambda = 2/3$. While the effects are a bit smaller for $\lambda = .5$ and a bit larger for $\lambda = 1$, the results do not change much.[34]

[34]As λ gets close to zero, the magnitude of the effects does change dramatically, largely because the interpretation of housing demand shocks changes. Since there was a small population increase during this

Finally, we show results for different values of ϕ. Changing the value of ϕ from $\frac{1}{2}$ to 1 has only a minor negative effect on the long-run effects. When we get to smaller values of ϕ, like 0.25, the effects become a bit smaller but are still qualitatively similar to our preferred estimates.

Overall, we view our estimates as relatively robust to different parameterizations.[35]

6.3 Location Demand Channel Projected onto Remote Work Variables

In the previous section, we showed that observed location demand shocks were related to variables we expected to be related to remote work. If we wish to consider only the effects of the location demand shocks that project onto these variables, we can revisit the analysis by using those shocks instead.

To carry out this analysis, we use the predicted values of location demand shocks from the previous section, rather than the observed location demand shocks from the data. Plugging in the numbers, the long-run effects of remote work are -.001 log-points from location demand. Numbers for CPI Cities and Expensive Metros can be found at the bottom of Table 1. This is about 40 percent of the size of the location demand channel that we calculated assuming all relative rent changes are the result of remote work.

We cannot do the same for housing demand shocks. The reason for this is that a cross-sectional regression only identifies the relative housing demand shocks correlated to remote work variables. This is fine for location demand shocks, since relative location demand shocks are what matters, but the formula for housing demand shocks depends on the average, which we cannot identify off of cross-sectional regressions.

6.4 Comparison to House Prices

To this point in the paper, we have only considered the effect of the remote work shock on rents and populations. However, a reader might reasonably be interested in how the remote work shock affected house prices for two reasons: first, because house prices are inherently interesting; and second, because it might serve as a robustness check for the model.

time period, if we assume that the housing stock was fixed and that people did not adjust their housing size, the only possible way to clear markets would be to assume that housing demand fell. Given that this does not correspond to the general fact that remote work increased housing demand, it is an argument against very small values of λ.

[35] In appendix A, we show that the parameters also do not affect the short-run values too much. In particular, under our preferred parameterization, the short-run effect of the housing demand channel is .07, and the short-run effect of the location demand channel is 0.

The model we presented in Section 4 did not include house prices and because of its simplicity, there is no obvious way to solve for house prices. In order to make progress on this point, we write down a discrete-time dynamic model that features house prices. Importantly, this new model nests the previous model, in the sense that period 0 and period 1 are the same, and the steady-state of the new model is the same as period 2 in the previous model.

The key features of the model that were not present in the simpler model from Section 4 are: (1) house prices are the present discounted value of rents; (2) housing depreciates each period and is replenished through housing investment that depends on house prices; (3) housing investment is subject to a time-to-build constraint; and (4) people re-optimize their housing consumption and location with a certain probability each period. Details can be found in Appendix C. Compared to models such as Favilukis, Mabille and Van Nieuwerburgh (2023), our model is relatively simple. For example, the agents in our model do not make forward-looking tenure choices. The main reason for variation in the price-to-rent ratio is changes in the interest rate, which is an important margin we hope to capture; however, this means that we do not capture much of the location variation in the price-to-rent ratio as confirmed by our empirical estimates.

Because the dynamic model nests the two time periods from the simple model as the initial shock and the long-run steady-state, the main "new" aspect of the dynamic model is that it is able to solve for the transition dynamics of rents, housing quantities, and populations. Solving for the transition dynamics of rents is particularly important because it allows us to calculate house prices as the present discounted value of rents. Since solving for house prices was the goal of the model, this is a crucial step.[36]

In the long-run steady-state of our model, house price and rent changes converge to the same values locally. If county A had an x log-point increase in rents, then county A's house prices also increased by x log-points. Hence, all the results we had previously shown for the long-run effects of remote work on rents would also apply as the long-run effects on house prices.

More interesting are some of the results regarding short-run house prices. While the model is not simple enough to solve in closed form for house prices, it is still easily linearizable, and we use Dynare (Adjemian, Bastani, Juillard, Mihoubi, Perendia, Ratto and Villemot, 2011) to solve for the short-run impact on house prices, which we can compare to the data. Since we use rents and not house prices to estimate the location and housing demand shocks,

[36]The transition dynamics themselves are not particularly interesting and behave as one might expect, with an initial impulse, followed by roughly exponential convergence to the new steady-state. While the full dynamic model is needed to calculate house prices, the dynamics themselves are largely uninteresting and are not the focus of our paper.

Table 2: House Price Results

	(1) Data (OLS)	(2) Data (2SLS)	(3) Baseline	(4) μ=100	(5) Interest Rate Shock	(6) Baum-Snow and Han
Rent Growth, Feb 2020-22	0.845***	0.998***	0.763***	0.993***	0.711***	0.899***
	(0.037)	(0.045)	(0.001)	(0.000)	(0.002)	(0.001)
Constant	0.145***	0.133***	-0.0128***	-0.0298***	0.154***	-0.00857***
	(0.004)	(0.005)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	490	483	2736	2736	2736	2736
R^2	0.519	0.501	0.995	1.000	0.968	0.999
Average House Price Change	0.194	0.194	0.040	0.040	0.203	0.054

The first two columns present show a regression of house price changes from Feb. 2020 to Feb. 2022 on rent changes over the same time period. Column (1) regresses Zillow house price changes on Zillow rent changes. Column (2) regresses Zillow house price changes on Zillow rent changes, using Costar rent changes as an instrument. Columns (3)-(6) show the model-implied house price changes on the data, under a variety of parameterizations. The baseline model is presented in Appendix C, and features house prices as the present discounted value of future rents, and slowly depreciating housing. We also consider a variety of alternative specifications. Column (4) assumes that $\mu = 100$ instead of $\mu = 1.07$ in the baseline simulation. Column (5) assumes that in addition to the housing demand and location demand shocks in our baseline model, that the economy is also hit with an interest rate shock, in which rates fall. Column (6) assumes that instead of our σ_i being the elasticities measured by Baum-Snow and Han (2022) times 3.23 as discussed in Section 4.2, that the σ_i are the Baum-Snow and Han (2022) elasticities without any adjustment. All regressions are weighted by 2019 populations. Robust standard errors in parentheses. $^*p < 0.05, ^{**} p < 0.01, ^{***} p < 0.001$

comparing the data and model predictions can serve as a check of the validity of the model, or show us what features might be missing from the model that are important for house prices in particular.

To analyze the effects on house prices, we regress the short-run changes in house prices on the short-run changes in rents. We can do this using both the model and the data, since the short-run changes in rents are the same in both the model and the data.

The results of this exercise are presented in Table 2. In column (3), we show a regression of house prices on rents, in our baseline calibration of the model. The regression coefficient is about 0.76 and the R^2 is above 0.99. This means that places that had larger increases in rents also had a higher increase in model-implied house prices, although the effect was not quite one-for-one. This coefficient being less than one is because people have strong idiosyncratic preferences over location, and so as more people move to the places that had rent increases in the long run, the relative rent changes need to be less big to make the marginal person indifferent. We can confirm this intuition by considering an alternative calibration where $\mu = 100$ and we see a coefficient on house prices of almost exactly 1.

How does this compare to the data? In column (1), we run the same regression of house prices on rents (excluding the counties for which we infer rents from house prices). We get a coefficient that is quite high, 0.845, which is a bit larger than our baseline specification, but still less than 1.

One concern with the regression in column (1) is measurement error.[37] If there is classi-

[37]Measurement error may also explain some of the lower R^2, although we also would attribute the $R^2 < 1$ to county-specific factors in prices and rents.

cal measurement error, we can correct the regression coefficient using instrumental variables, where the instrument is another estimate of rent changes that is uncorrelated to the measurement error of Zillow. We use an estimate of the rent changes from Costar as our instrument. The F-statistic on the first-stage regression is above 300. The point estimate of the two stage least squares regression, shown in column (2), is almost exactly 1, although with wide standard errors.

We also consider an alternative calibration of the model in column (6), using the unadjusted Baum-Snow and Han (2022) housing supply elasticities. Here, the coefficient is larger than in our baseline model, near the OLS, but still below 1.

Given that the across all four columns (1)-(4) and (6), there is a very high coefficient less than 1 when regressing house prices on rents, we think the model is generally consistent with the data with regards to the cross-sectional predictions regarding house prices.

However, there is another major difference between the data and the baseline model, which is that house prices in the data increased by a significant amount compared to house prices in the model. To see this, compare the average house price change in columns (2) and (3). While the regression is limited by the number of counties for which we observe rent, the average house price change at the bottom of the table is for a consistent sample of counties. In the data, house prices rose by nearly 20 percent, while the model has only a small increase.

The model predicts short-run house prices should rise less than short-run rents because long-run rents rise less than short-run rents, and house prices depend on both short-run and long-run rents; therefore, the data strongly suggests our dynamic model is missing something.[38] A natural candidate for what the model might be missing is a change in the interest rate. In column (5), we add an interest rate shock to the model which is described in Appendix C. With the interest rate shock, the cross-sectional predictions of the model do not change much—the regression coefficient is still about three-quarters, and the R^2 is still close to 1—but the constant term is much closer to the one in the data. Admittedly, we impose a larger interest rate shock than is observed in the data, but our main point is that the constant term may react to changes in credit markets, of which there were many between February 2020 and February 2022; therefore, the different constant terms should not be taken as a rejection of the model.

[38]One possibility would be that there was significant substitution between owner-occupied housing to rental housing Halket, Nesheim and Oswald (2020); Gete and Reher (2018); Greenwald and Guren (2021). However, Loewenstein and Willen (2023) establishes that prices on rental housing moved in similar ways to prices on owner-occupied housing. Hence, we do not focus on theories of owner-occupied and rental housing substitution, but rather, we focus on explaining house price movements that are the result of changes in the future rents or discount factors.

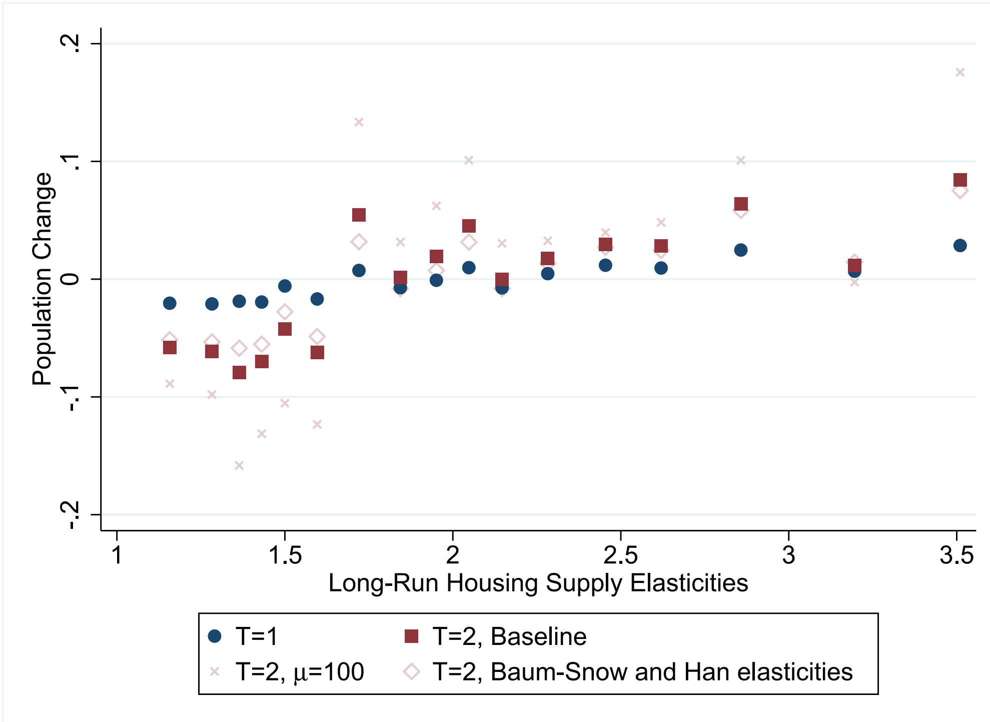


Figure 6: A binned scatter plot of the short- and long-run population changes due to housing and location demand shocks, by housing supply elasticity

6.5 Cross-Sectional Effects on Population

Our model also has implications for which regions will gain and lose population in the long-run. In the long-run, housing supply adjusts to changes in location demand, which increases the equilibrium population in places where housing supply increases. We show the long-run effects on populations, by bins of housing supply elasticity in Figure 6. The figure shows the average population growth in response to the location and housing demand shocks, for counties binned by housing supply elasticity. The most inelastic counties lost population in the short-run, and are predicted to lose even more population in the long-run. The most elastic counties gained population in the short-run, and those effects are also expected to be larger in the long-run.

Under other parameterizations, the population predictions may be more or less extreme. Intuitively, when $\mu \to \infty$, people are more mobile in response to rent changes, and there should be more long-run population movements. Similarly, when housing supply is less elastic (i.e. when we use the unadjusted Baum-Snow and Han (2022) elasticities), then there will be less long-term population movement since the housing supply will adjust less.

We can also calculate how the house price or the housing supply elasticity of the average American will change in both the short- and the long-run. In 2019, the average American lived in a county that had a 0.688 supply elasticity (using the Baum-Snow and Han (2022) measure), had a Zillow home value index of $309,987, and had a population density of 1659 people per square mile. The short-run effect of population changes was to change those numbers to 0.690, $308,129, and 1597 people per square mile, respectively. But the long-run effect of these shocks is that people will move to places that had 0.695 elasticity, $303,772 Zillow home value index, and 1480 people per square mile in 2019.[39] The long-run effect on population movements is that the average American lives in a county that is 1.0 percent more elastic, 2.0 percent cheaper, and 10.2 percent less dense in 2019. This is in addition to the fact that we expect housing costs to increase by 1.5 percentage points on net, and that outmigrants will affect the density of the densest places.

6.6 Scenarios for the future of remote work

To this point, our assumption has been that the model-implied shocks to housing demand and location demand were fully realized and permanent, and we have used the lens of the model to extrapolate what the long-term effects of those shocks were. As with any predictive exercise, a reader may disagree on the expected future path of the housing and location demand shocks. Our model is tractable enough that it is relatively straightforward to map different assumptions about the future of remote work onto the predictions.

In this section, we consider a few different ones: first, we ask what happens if the housing demand shocks are more temporary because they were actually due to factors other than remote work; and second, we ask what happens if remote work continues to evolve and the shocks are larger in the long-run. Finally, we ask what happens if remote work not only becomes more important, but also is no longer tied at all to office location, and there is an even bigger shift to high-amenity low-rent places. All of the results are presented in Table 3.

6.6.1 How much of housing demand is remote work?

While Section 5.2 argues that the majority of the location demand channel is driven by observable variables that relate to remote work, we cannot make a similar argument regarding the housing demand channel. The reason for this is that the location demand channel relies on the cross-section of location demand shocks, so only the relative exposure to remote work matters, which is what we can identify in a regression. In contrast, calculating the size of

[39] Importantly, this is not a claim about the direction that house prices will move—as in it should not matter for calculating a price index—but is a helpful summary statistic for understanding the movement of population.

Table 3: Alternative Scenarios

Region	(1) Total	(2) Location Demand Channel	(3) Housing Demand Channel
		Baseline	
National	.015	-.003	.018
CPI Cities	.009	-.01	.018
Expensive Metros	-.013	-.035	.022
		60% Housing Demand	
National	.008	-.003	.011
CPI Cities	.001	-.01	.011
Expensive Metros	-.022	-.035	.013
		700% Location Demand	
National	-.001	-.019	.018
CPI Cities	-.049	-.068	.018
Expensive Metros	-.224	-.246	.022
		200% Amenities	
National	.014	-.003	.018
CPI Cities	.006	-.012	.018
Expensive Metros	-.02	-.042	.022

Notes: Estimates correspond to alternative scenarios considered in Section 6. See text for details.

the housing demand shocks requires taking a stand on their absolute size, which we cannot do without auxiliary assumptions.

It makes sense to consider the long-run if the housing demand changes that we have observed over the last few years are due to temporary factors,such as expansionary fiscal policy that has spurred spending on durable goods.

If none of the housing demand shocks are due to remote work, then the long-run effect of remote work is simply the location demand channel, a 0.003 log-point decrease in rents. The linearity of our model helps calculate intermediate values as well. If x percent of the housing demand shocks are due to remote work, then the total effect will be 0.015 times x percent. If you think only 20 percent is due to remote work, you would believe that the net effect is 20 percent times 0.015, plus the location demand channel, for a net effect very close to zero. If you think that 60 percent of the increase in recent house prices is due to remote work (as in Mondragon and Wieland, 2022), you would think the net effect is 0.009, plus the location demand channel, for a net effect of 0.006.

6.6.2 Expansion of remote work

Our location demand channel also scales linearly with the size of the shock. If we wish to consider a world in which the relative location demand shocks increase by a factor of 7, we can do that. In this case, we simply multiply the location demand channel by 7, yielding a location demand channel of 0.019, which would make the net effect basically zero. In this scenario, the location demand effect for CPI rents and aggregate rents is also multiplied by a factor of 7.

6.6.3 Greater flexibility of location demand

When projecting the changes in rents onto remote work variables, it is clear that high-amenity, low-rent places saw increases in location demand in the short-term. One possible counterfactual is to consider that if remote work becomes even easier, people will move even further from their jobs and into high-amenity places—especially those high-amenity *and* low-rent places.

Regression (22) showed that higher-amenity places (and particularly higher-amenity places with lower house prices) had larger location demand shocks. If we take those coefficients to be causal and double the impact of the amenities by doubling those coefficients while leaving everything else the same, then we can recalculate the long-run effects using those new shocks. The location demand channel becomes more negative modestly, with slightly larger effects for CPI cities and Expensive Metros. This can be seen in the last panel of Table 3.

7 Conclusion

In this paper, we compare the short- and long-run effects of remote work, using a simple model of housing markets within the United States. We show that even though remote work has increased rents in the short-run, they are likely to decline going forward and in the long-run may end up lower than pre-pandemic.

References

Adjemian, Stéphane, Houtan Bastani, Michel Juillard, Ferhat Mihoubi, George Perendia, Marco Ratto, and Sébastien Villemot, "Dynare: Reference manual, version 4," 2011.

Albouy, David, Gabriel Ehrlich, and Yingyi Liu, "Housing demand, cost-of-living inequality, and the affordability crisis," Technical Report, National Bureau of Economic Research 2016.

Althoff, Lukas, Fabian Eckert, Sharat Ganapati, and Conor Walsh, "The geography of remote work," *Regional Science and Urban Economics*, 2022, *93*, 103770.

Ambrose, Brent W, N Edward Coulson, and Jiro Yoshida, "The repeat rent index," *Review of Economics and Statistics*, 2015, *97* (5), 939–950.

Barrero, Jose Maria, Nicholas Bloom, and Steven J Davis, "COVID-19 is also a reallocation shock," Technical Report, National Bureau of Economic Research 2020.

Bartik, Alexander W, Zoe B Cullen, Edward L Glaeser, Michael Luca, and Christopher T Stanton, "What jobs are being done at home during the COVID-19 crisis? Evidence from firm-level surveys," Technical Report, National Bureau of Economic Research 2020.

Baum-Snow, Nathaniel and Lu Han, "The microgeography of housing supply," 2022.

Behrens, Kristian, Sergey Kichko, and Jacques-François Thisse, "Working from home: Too much of a good thing?," *Available at SSRN 3768910*, 2021.

Blinder, Alan, "Fear of Offshoring," *CEPS Working Paper No. 119*, 2005.

Brueckner, Jan, Matthew E Kahn, and Gary C Lin, "A new spatial hedonic equilibrium in the emerging work-from-home economy?," Technical Report, National Bureau of Economic Research 2021.

Brynjolfsson, Erik, John J Horton, Adam Ozimek, Daniel Rock, Garima Sharma, and Hong-Yi TuYe, "COVID-19 and remote work: An early look at US data," Technical Report, National Bureau of Economic Research 2020.

Bureau of Labor Statistics, "Updating the rent sample for the CPI housing survey," *Monthly Labor Review*, 2013.

Chatelier, Henri Louis Le, "Sur un énoncé général des lois des équilibres chimiques," *Comptes Rendus Chimie*, 1884, *99.*

Davis, Morris A, Andra C Ghent, and Jesse M Gregory, "The work-from-home technology boon and its consequences," Technical Report, National Bureau of Economic Research 2021.

Delventhal, Matt and Andrii Parkhomenko, "Spatial implications of telecommuting," *Available at SSRN 3746555*, 2020.

Delventhal, Matthew J, Eunjee Kwon, and Andrii Parkhomenko, "JUE Insight: How do cities change when we work from home?," *Journal of Urban Economics*, 2022, *127*, 103331.

Dingel, Jonathan I and Brent Neiman, "How many jobs can be done at home?," *Journal of Public Economics*, 2020, *189*, 104235.

Fajgelbaum, Pablo D, Eduardo Morales, Juan Carlos Suárez Serrato, and Owen Zidar, "State Taxes and Spatial Misallocation," *The Review of Economic Studies*, 09 2019, *86* (1), 333–376.

Favilukis, Jack, Pierre Mabille, and Stijn Van Nieuwerburgh, "Affordable housing and city welfare," *The Review of Economic Studies*, 2023, *90* (1), 293–330.

Gete, Pedro and Michael Reher, "Mortgage supply and housing rents," *The Review of Financial Studies*, 2018, *31* (12), 4884–4911.

Glaeser, Edward L and Joseph Gyourko, "Urban decline and durable housing," *Journal of Political Economy*, 2005, *113* (2), 345–375.

_ and _ , "Housing dynamics," 2006.

Greenwald, Daniel L and Adam Guren, "Do credit conditions move house prices?," Technical Report, National Bureau of Economic Research 2021.

Gupta, Arpit, Vrinda Mittal, Jonas Peeters, and Stijn Van Nieuwerburgh, "Flattening the curve: pandemic-induced revaluation of urban real estate," *Journal of Financial Economics*, 2021.

Halket, Jonathan, Lars Nesheim, and Florian Oswald, "The housing stock, housing prices, and user costs: The roles of location, structure, and unobserved quality," *International Economic Review*, 2020, *61* (4), 1777–1814.

Howard, Greg 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, *124*, 103369.

Hsieh, Chang-Tai and Enrico Moretti, "Housing constraints and spatial misallocation," *American Economic Journal: Macroeconomics*, 2019, *11* (2), 1–39.

Kolko, Jed, "Where COVID19 death rates are highest — May 13 update," 2020. Accessed July 29, 2022. http://jedkolko.com/2020/04/15/where-covid19-death-rates-are-highest/.

Liu, Sitian and Yichen Su, "The impact of the COVID-19 pandemic on the demand for density: Evidence from the US housing market," *Economics Letters*, 2021, *207*, 110010.

Loewenstein, Lara and Paul S Willen, "House Prices and Rents in the 21st Century," National Bureau of Economic Research Working Paper 2023.

Mertens, Karel, Adam Blandin, and Alexander Bick, "Work from home before and after the covid-19 outbreak," 2022.

Mondragon, John A and Johannes Wieland, "Housing Demand and Remote Work," Technical Report, National Bureau of Economic Research 2022.

Mongey, Simon, Laura Pilossoph, and Alexander Weinberg, "Which workers bear the burden of social distancing?," *The Journal of Economic Inequality*, 2021, *19* (3), 509–526.

Monte, Ferdinando, Stephen J Redding, and Esteban Rossi-Hansberg, "Commuting, migration, and local employment elasticities," *American Economic Review*, 2018, *108* (12), 3855–90.

Ozimek, Adam, "Overboard on Offshore Fears," *Available at SSRN: 3777307*, 2019.

_ , "The future of remote work," *Available at SSRN 3638597*, 2020.

_ , "The New Geography of Remote Work," *Available at* `https://adamozimek.com/admin/pdf/EconReport_RemoteWorkersnotheMove2_Feb2022.pdf`, 2022.

_ **and Eric Carlson**, "Remote Work and Household Formation," 2023.

Parkhomenko, Andrii, "Local causes and aggregate implications of land use regulation," *Available at SSRN 3739183*, 2020.

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

Ramani, Arjun and Nicholas Bloom, "The Donut effect of COVID-19 on cities," Technical Report, National Bureau of Economic Research 2021.

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.

Rosenthal, Stuart S, William C Strange, and Joaquin A Urrego, "JUE insight: Are city centers losing their appeal? Commercial real estate, urban spatial structure, and COVID-19," *Journal of Urban Economics*, 2022, *127*, 103381.

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

Schubert, Gregor, "House Price Contagion and US City Migration Networks," *Working Paper*, 2022.

Stanton, Christopher and Pratyush Tiwari, "Housing Consumption and the Cost of Remote Work," 2021.

United States Department of Agriculture Economic Research Service, "Natural Amenities Scale," 2019. Accessed July 29, 2022. https://www.ers.usda.gov/data-products/natural-amenities-scale/.

A Appendix

In this appendix, we show some supplementary figures.

Figure A1 shows the population density of counties for which Baum-Snow and Han (2022) does and does not calculate housing supply elasticities. It also shows the relationship between population density and elasticity. It justifies our assumption to treat counties for which Baum-Snow and Han (2022) does not calculate elasticities as very elastic.

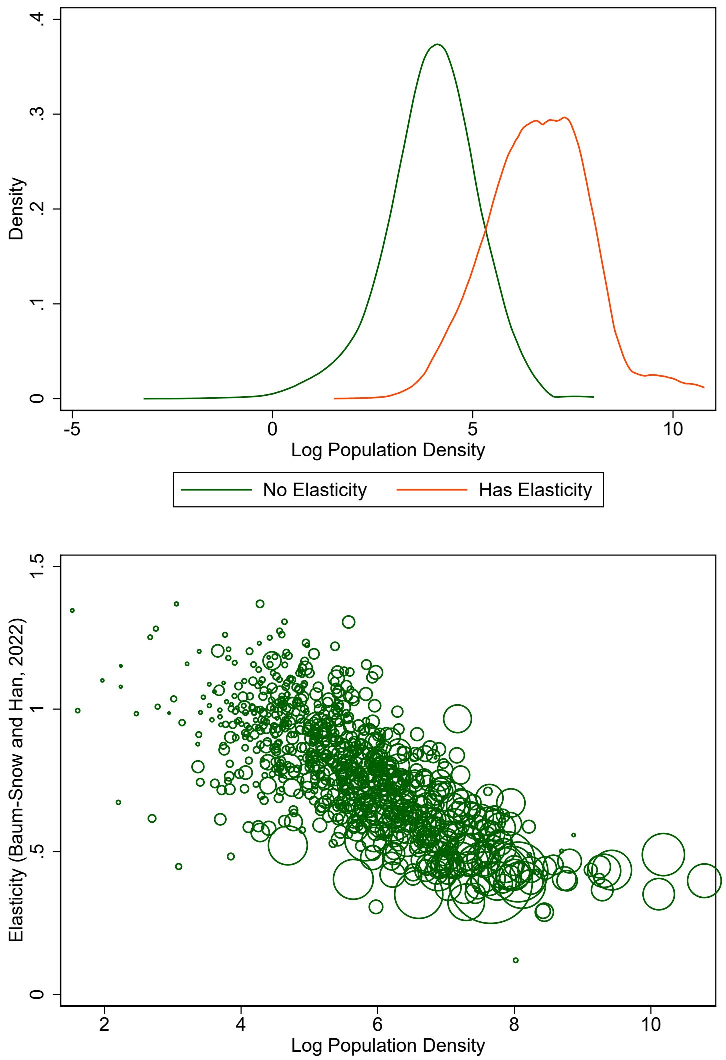


Figure A1: Upper panel: Log density of counties, with and without Baum-Snow and Han (2022) elasticities. Lower panel: Scatter plot with the relationship between population density and housing supply elasticity.

In Figure A2, we show the rent growth versus elasticity, splitting the sample by color to highlight which counties are based on Zillow data and which ones are based on our estimation of a regression of rents on house prices.

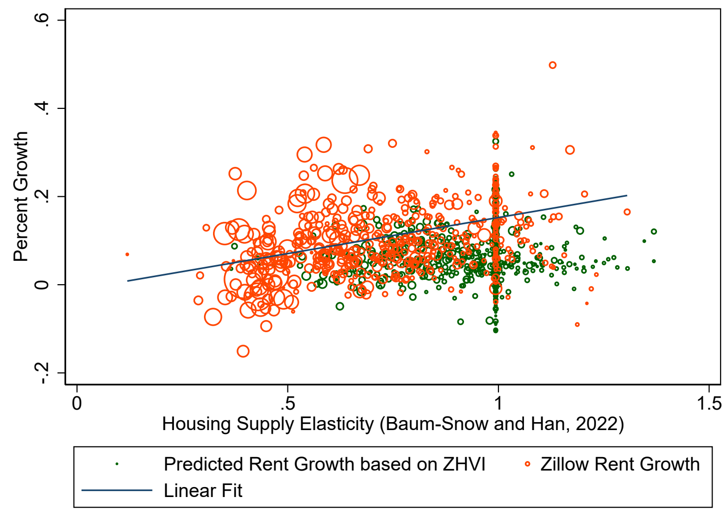


Figure A2: Rent Growth, 2020-2022

In Table A1, we show the regression corresponding to (22). Most of the remote work variables are highly correlated to one another, so interpreting any individual coefficient is difficult.

In Figure A3, we show the analog to Figure 4, but using population data instead. In Figure A4, we show the analog to Figure 4, but using rent data instead.

Table A1: Projecting Rent Changes onto Remote Work variables

	(1) Rent Growth	(2) Population Growth	(3) Location Demand Shock
Amenity Index	0.0104***	0.00430***	0.0197***
	(0.000808)	(0.000399)	(0.00136)
Log House Price, Feb 2000	0.0557***	-0.0104*	0.0387*
	(0.00900)	(0.00445)	(0.0152)
Amenity Index × Log House Price, Feb 2000	-0.0174***	-0.00472***	-0.0281***
	(0.000668)	(0.000330)	(0.00113)
Work From Home Share	0.102	-0.108***	-0.106
	(0.0601)	(0.0297)	(0.101)
Work From Home Share within 25 miles	-0.295***	-0.0101	-0.336*
	(0.0837)	(0.0414)	(0.141)
Relative House Price within 25 miles	-0.124	0.0369	-0.0587
	(0.0778)	(0.0385)	(0.131)
Work From Home Share within 25 miles × Relative House Price within 25 miles	0.185	-0.0867	0.0246
	(0.198)	(0.0978)	(0.334)
Work From Home Share within 50 miles	0.378***	0.0132	0.431**
	(0.0878)	(0.0434)	(0.148)
Relative House Price within 50 miles	0.160*	0.0156	0.203
	(0.0669)	(0.0331)	(0.113)
Work From Home Share within 50 miles × Relative House Price within 50 miles	-0.242	-0.0238	-0.306
	(0.164)	(0.0813)	(0.278)
Work From Home Share within 100 miles	-0.236*	0.241***	0.230
	(0.0997)	(0.0493)	(0.168)
Relative House Price within 100 miles	0.252***	0.107**	0.482***
	(0.0695)	(0.0343)	(0.117)
Work From Home Share within 100 miles × Relative House Price within 100 miles	-0.770***	-0.221**	-1.265***
	(0.169)	(0.0836)	(0.285)
Work From Home Share within 250 miles	-0.735***	-0.318***	-1.422***
	(0.158)	(0.0782)	(0.267)
Relative House Price within 250 miles	-0.177	-0.0285	-0.246
	(0.0987)	(0.0488)	(0.167)
Work From Home Share within 250 miles × Relative House Price within 250 miles	0.407	0.0207	0.477
	(0.241)	(0.119)	(0.406)
Work From Home Share within 500 miles	-0.584***	0.118	-0.389
	(0.170)	(0.0838)	(0.286)
Relative House Price within 500 miles	0.694***	0.403***	1.548***
	(0.117)	(0.0577)	(0.197)
Work From Home Share within 500 miles × Relative House Price within 500 miles	-1.858***	-0.981***	-3.950***
	(0.292)	(0.145)	(0.493)
Constant	0.623***	0.0272	0.721***
	(0.0578)	(0.0286)	(0.0976)
Observations	2716	2715	2715
R^2	0.382	0.204	0.374
F	87.58	36.37	84.64

Standard errors in parentheses. Changes measured using log changes from February 2020 to February 2022. Regression weighted by county population in 2019. $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

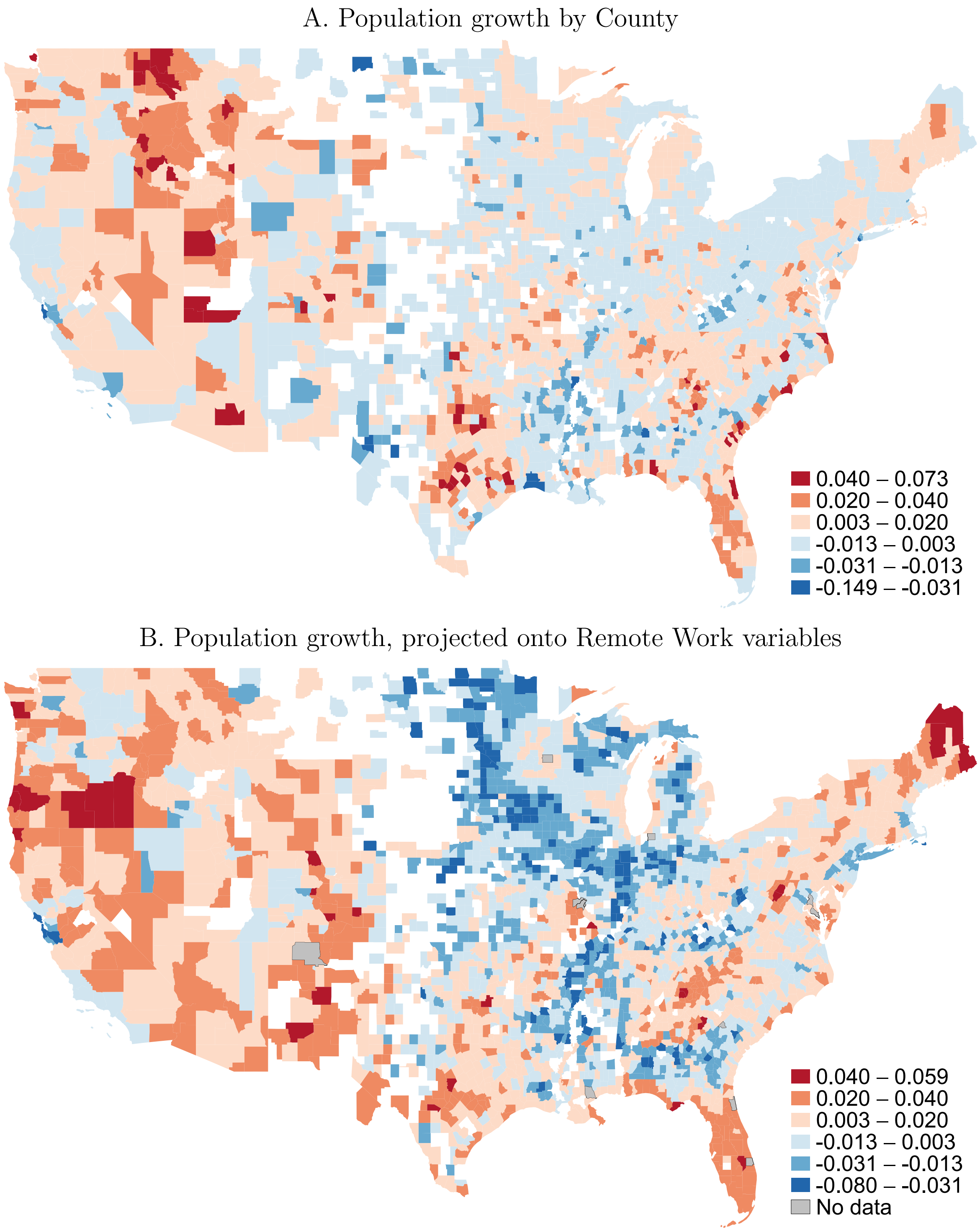
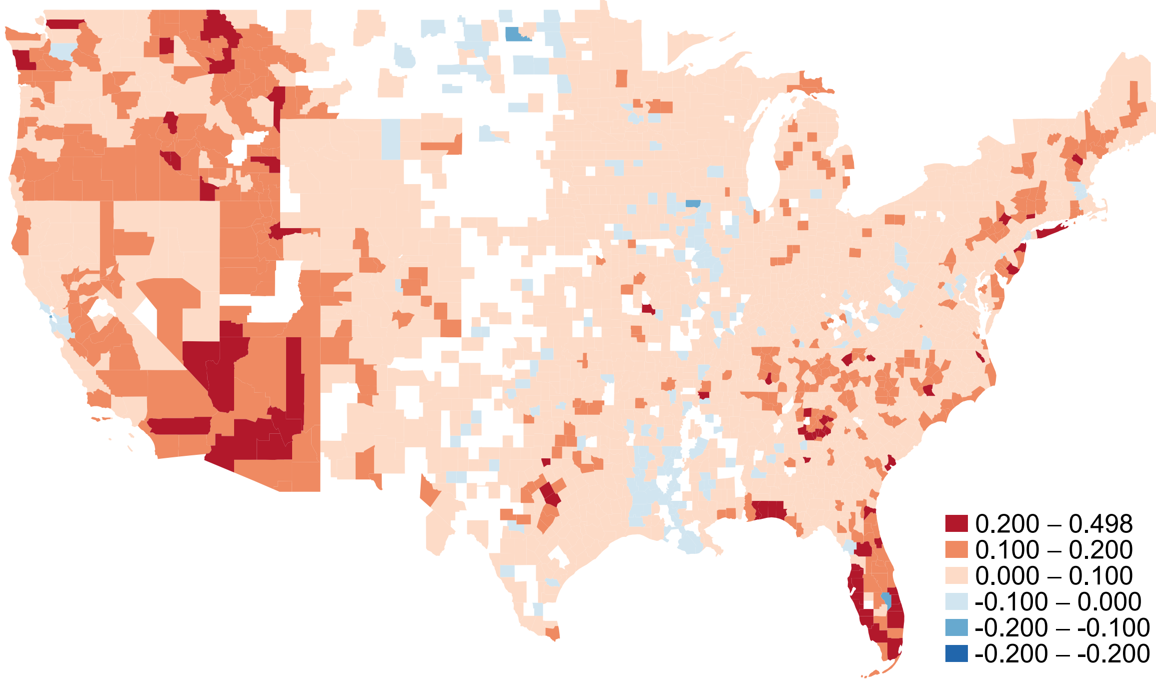


Figure A3: This figure shows population changes and population changes projected onto remote work shocks. Panel A is a choropleth map showing the population change at the county level. Panel B shows the population change projected onto remote work measures estimated using Equation (22). The colors are on the same scale in both maps.

A. Rent changes by County



B. Rent changes, projected onto Remote Work variables

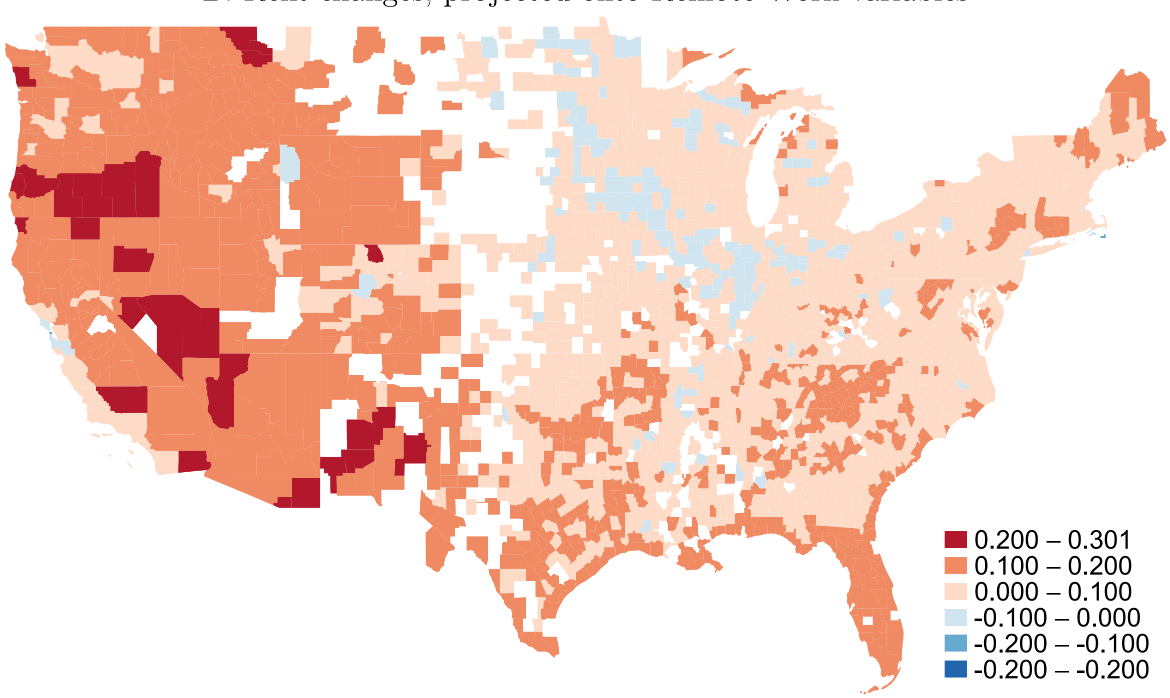


Figure A4: This figure shows real rent changes and real rent changes projected onto remote work shocks. Panel A is a choropleth map showing the real rent change at the county level. Panel B shows the real rent change projected onto remote work measures estimated using Equation 22. The colors are on the same scale in both maps.

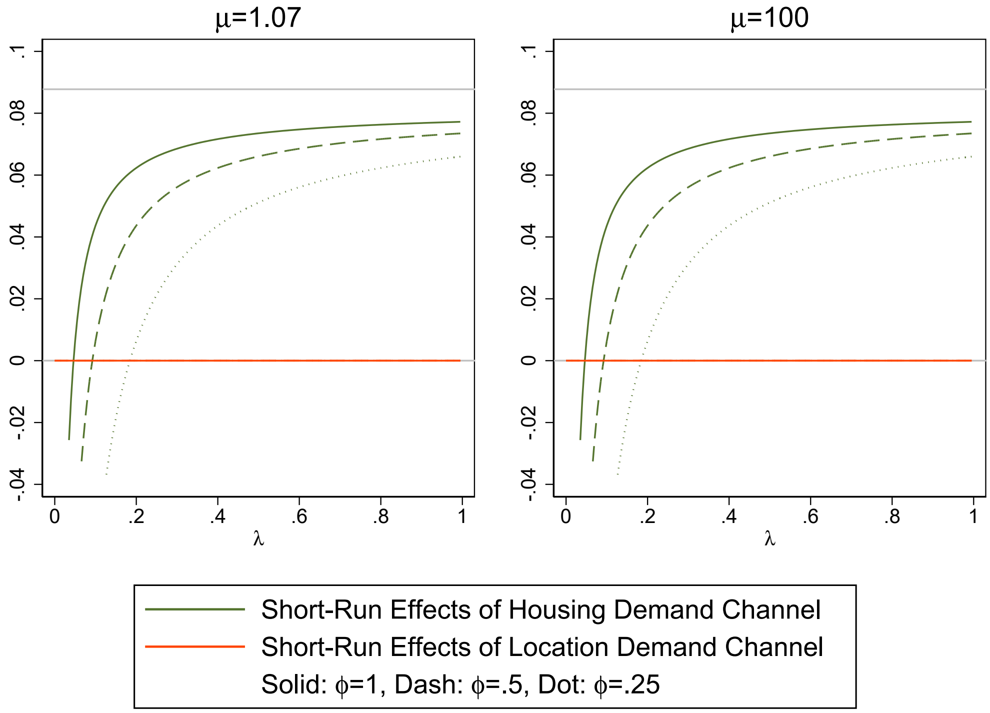


Figure A5: Parameter Sensitivity, short-run effects

In Figure A5, we show that the choice of parameters does not affect the size of the location demand channel or the housing demand channel too much. The short-run location demand channel is always 0, regardless of μ, λ, and ϕ.

Like the long-run housing demand channel, the short-run housing demand channel also depends on λ and ϕ, but the fact that it explains most of the increase in rents is not going to be affected much by the choice of parameters, as long as λ is sufficiently high.

B Validating the Address Change Data

In this appendix, we validate our usage of the address change data to approximate population growth. As in the paper, we look at population growth at the county level. In this appendix, we focus on the period from July 2020 to July 2021, since the Census Bureau also produces population growth estimates during this time period.

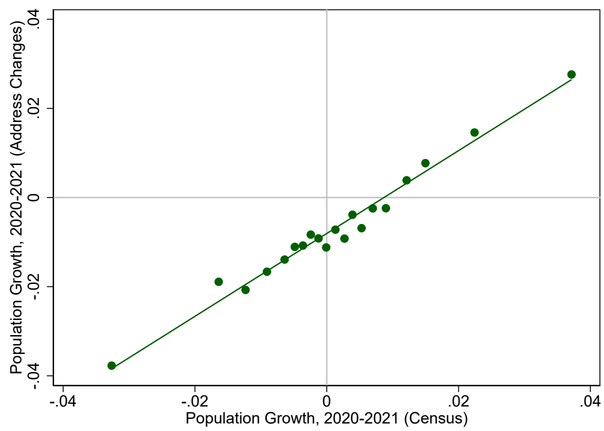


Figure A6: A binned scatter plot of population growth implied by address changes versus Census-estimated population growth

To validate the data, we run a regression of the population growth implied by the address change data on the Census data over the same time period. If the Census data were perfectly accurate and the address change data was a noisy measure of population growth, then the coefficient should have a coefficient of 1. Since we care more about the growth rate of large counties, we weight by 2020 populations.

The regression has a coefficient of 0.93, with a standard error of 0.014. While statistically significantly less than 1, it is economically quite close. The R^2 of the regression is 0.60, so there is some noise. Nonetheless, since our covariance estimates are not biased by noise, we view this exercise as confirming that the address change data is suitable as an estimate of the population growth of counties.

We also show a binned scatter plot of the two measures of population growth to show that their relationship is linear.

C Dynamic Model to Estimate House Prices

In this appendix, we present a discrete-time infinite-horizon dynamic model with many similar features as the three-period model presented in the main text. In fact, the model is designed so that period 0 and period 1 are identical to the three-period model, and the long-run steady-state of this appendix's model is equivalent to period 2 in the three-period model. Therefore, all the claims regarding the short- and long-run effects of remote work on housing markets will also hold in this model.

The primary reason we write down this model is to be able to make claims about house prices. In this appendix's model, we can measure house prices as the present discounted value of rents a la Poterba (1984). Supplemental reasons to have this model include that we can allow housing construction to react to the price of housing rather than rents, which may be a more natural assumption. Finally, we are able to derive the rationale for why we adjust the Baum-Snow and Han (2022) elasticities, which are measured over a 10-year horizon, when we want to think about the long-run of housing markets.

C.1 Dynamic Model

Time is discrete, $T \in \{0, 1, 2, ...\}$. Each period corresponds to 2 years.

As in $T = 1$ of the three-period model, a fraction ϕ of people choose the amount of housing and the location of where to live in each period. Agents have the same preferences as they do in the main text, and they make this choice myopically.

Therefore, population and housing consumption evolve as

$$\begin{aligned} d \log L_{it} &= (1-\phi) d \log L_{it-1} - \phi \mu d \log r_{it} + \phi(\eta_i - d\tilde{u}_t) \\ d \log h_{it} &= (1-\phi) d \log h_{it-1} - \phi \lambda d \log r_{it} + \phi \epsilon_{it} \end{aligned}$$

Note that in period 1, when $d \log L_{i0}$ and $d \log h_{i0}$ are both zero, this reduces to the equation in the main text.

Also note that the steady-state of these equations, in which we set $d \log L_{it} = d \log L_{it-1}$ and $d \log h_{it} = d \log h_{it-1}$ correspond to the equations from $T = 2$ in the main text.

Housing in each location is dynamically given by the following capital accumulation function:

$$H_{it} = (1-\delta) H_{it-1} + Z_i \mathbb{E}_{t-1}[p_{it}]^{\sigma_i}$$

where σ_i is the short-run housing investment elasticity, δ is the depreciation rate, and Z_i is some city-specific constant. Note that we assume that housing requires one period to build, so the relevant price for housing investment is last period's expectation of this year's price.

In the first period, at the time of an unanticipated shock, there is no additional housing investment, so if the economy is at steady-state, then $H_{i1} = H_{i0}$. This corresponds to our assumption of $d \log H_{it} = 0$ at time $T = 1$ in the main text.

Housing is priced by risk-neutral absentee landlords who discount the future at interest rate R.

$$p_{it} = \sum_{s=t}^{\infty} \left(\frac{1-\delta}{1+R}\right)^{s-t} r_{it}$$

The long-run steady-state of this model is:

$$p_i = \frac{1+R}{R+\delta} r_i$$

and

$$H_i = Z_i \left(\frac{1+R}{R+\delta}\right)^{\sigma_i} \frac{1}{\delta} r_i^{\sigma_i}$$

Note that this second equation shows that the long-run housing supply elasticity is σ_i. This corresponds to $T = 2$ in the model.

C.2 Calibrating Elasticities

In the model, σ_i is not the ten-year elasticity. It can be interpreted as the short-run investment elasticity, but it is also the long-run elasticity of housing supply. The elasticities from Baum-Snow and Han (2022) are ten-year elasticities, though, so this must be reconciled.

To do this, we will start by calculating the 10-year housing supply elasticity in our model. Consider the evolution of housing quantity over 10 years:

$$H_{it+5} = (1-\delta)^5 H_{it} + \sum_{s=0}^{4} (1-\delta)^s Z_i p_{it+s}^{\sigma_i}$$

Recall that a period is two years in our model.

We can log-linearize the relationship around the steady-state of H_{it}:

$$d \log H_{it+5} \approx (1 - (1-\delta)^5) \sigma_i d \log p_i$$

where $d \log p_i$ is the log increase in house prices that is assumed to be constant over the ten-years.[40]

Remember that this ten-year elasticity is what Baum-Snow and Han (2022) is measuring. To translate this to a long-run elasticity, we have to multiply by

$$\sigma_i = \sigma_{\text{Baum-Snow and Han}} \frac{1}{1-(1-\delta)^5}$$

[40] To see this, note that in steady-state, $(1-(1-\delta)^5) H_{it} = \sum_{s=0}^{5} (1-\delta)^s Z_i p_{it+s}^{\sigma_i}$.

If we take $1-\delta = (1-0.03636)^2$, which is based on depreciation you can deduct on your taxes, but which is a bit higher than many estimates of housing depreciation (Glaeser and Gyourko (2005) also suggest 0.035 for the period from 1980-2000),[41] then the correct adjustment is:

$$\sigma_i = 3.23\ \sigma_{\text{Baum-Snow and Han}}$$

We arrive at this expression using log-linearization, which we discuss in Appendix Section C.2. Note that using a high-depreciation rate is conservative for our exercise, in that it leads to less elastic housing supply in the long-run. Smaller values for δ would lead a bigger number than 3.23 in the above equation.

Transition Equations

The overall model can be summarized by the following dynamic equations:

$$\begin{aligned}
d\log p_{it} &= \frac{R+\delta}{1+R} d\log r_{it} + \frac{1-\delta}{1+R}\mathbb{E}_t d\log p_{it+1} \\
d\log H_{it} &= (1-\delta) d\log H_{it-1} + \delta\sigma_i \mathbb{E}_{t-1} d\log p_{it} \\
d\log L_{it} &= (1-\phi) d\log L_{it-1} - \phi\mu d\log r_{it} + \phi(\eta_i - d\tilde{u}_t) \\
d\log h_{it} &= (1-\phi) d\log h_{it-1} - \phi\lambda d\log r_{it} + \phi\epsilon_{it} \\
d\log H_{it} &= d\log h_{it} + d\log L_{it} \\
0 &= \mathbb{E} d\log L_{it}
\end{aligned}$$

As noted, the steady-state of the above system of equations is $T = 2$ in the main text, and the first period of the above system of equations is $T = 1$.

We can use this model to calculate the change in house prices in the first period, and compare it to the data, under different parameter assumptions.[42]

[41] Glaeser and Gyourko (2005) give different depreciation rates for each decade from 1920 to 2000, ranging from 0.02 to 0.113. However, six out of eight of them are between 0.02 and 0.048. They also estimate depreciation over multiple decades and find much lower numbers, ranging from 0.016 to 0.039. Our calibration of 0.03636 is within the range of their values, on the slightly higher end, leading to more conservative estimates of the long-run differences.

[42] In practice, we use Dynare (Adjemian et al., 2011) to estimate this, since it is a system of $5N + 1$ dynamic equations, where N is the number of counties in the United States, making it infeasible to solve analytically for any of the relevant quantities.

C.3 Interest Rate Extension

To this point, the model in this section featured a fixed interest rate. However, this is easy to relax. To allow for a dynamic interest rate, we can replace the house price equation with

$$p_{it} = r_{it} + \frac{1-\delta}{1+R_t}\mathbb{E}p_{it+1}$$

Linearizing this equation gives us:

$$d\log p_{it} = \frac{R+\delta}{1+R}d\log r_t + \frac{1-\delta}{1+R}\mathbb{E}d\log p_{it+1} - \frac{1-\delta}{(1+R)^2}dR_t$$

where R is the steady-state value of R_t.

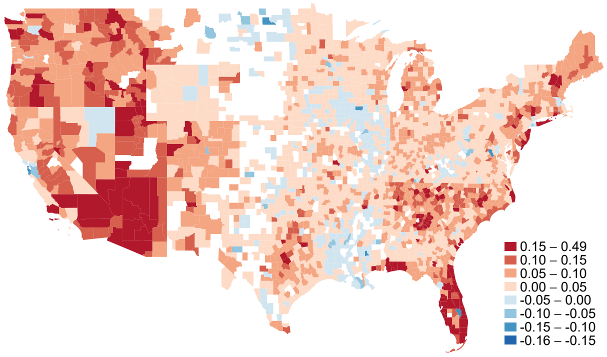
We can close the model by assuming an AR(1) process for interest rates.

$$dR_t = \rho dR_{t-1} + v_t$$

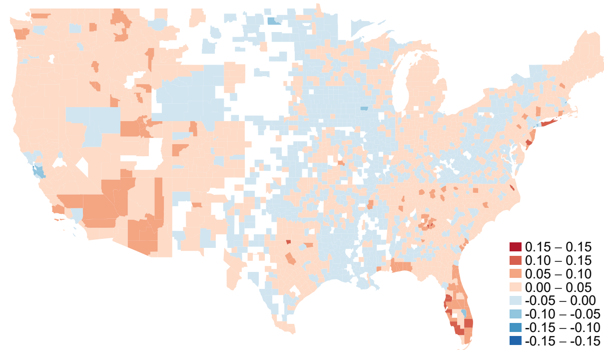
To match the increase in house prices, we assume a fall of interest rates of $v_1 = -.06$ and a persistence of $\rho = 0.95$. Keep in mind that the time period is 2 years, so this corresponds to a 3 percentage-point decline in the real rate with an annual persistence parameter of 0.975. While this is larger than we see in the data, we are aiming to capture a general relaxation of credit conditions which we do not try to model fully because that is not the purpose of our paper.

D Maps

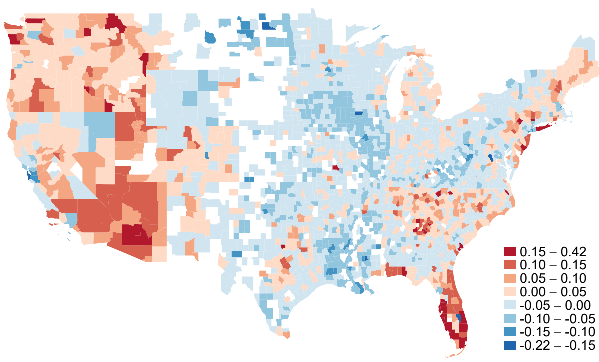
In this appendix, we show the changes in rents and population, in the short run, in the long run, and in the long run under alternative calibrations of our model. In each map, increases are colored red, and shaded darker for larger increases, while decreases are blue, and shaded darker for more negative decreases.



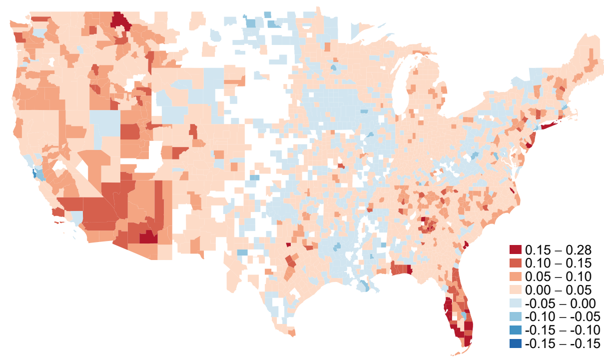
(a) Rent Changes, $T = 1$



(b) Rent Changes, $T = 2$

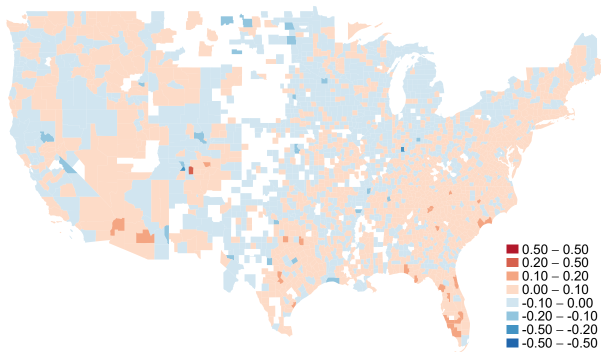


(c) Rent Changes, $T = 2$ when $\mu = 100$

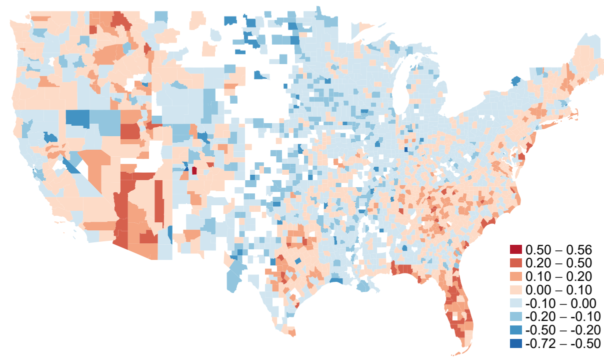


(d) Rent Changes, $T = 2$ when using Baum-Snow and Han (2022) elasticities

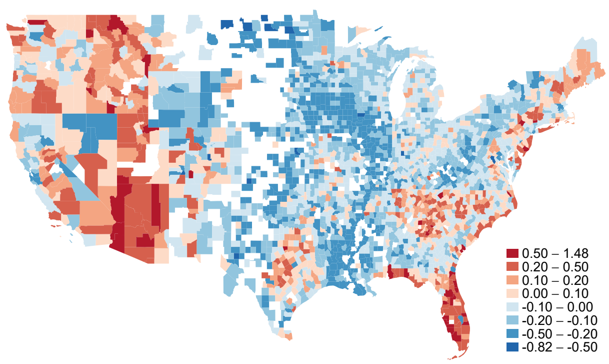
Figure A7: Rent changes, by county. Red counties experienced rent increases and blue counties experienced rent decreases. More intense colors are more positive or negative. Panel (a) shows the rent changes in the first period, corresponding to February 2022. Panel (b) shows the rent changes predicted by the model in the long-run. Panel (c) shows the rent changes in the long-run when the model is alternatively parameterized using $\mu = 1$. Panel (d) shows the rent changes in the long-run when the model is alternatively parameterized using housing supply elasticities from Baum-Snow and Han (2022), unadjusted for the fact that they are 10-year elasticities only. The same scaling is used in each panel so that the long-run can be visually compared to the short-run, and the different parameterizations can be compared to one another.



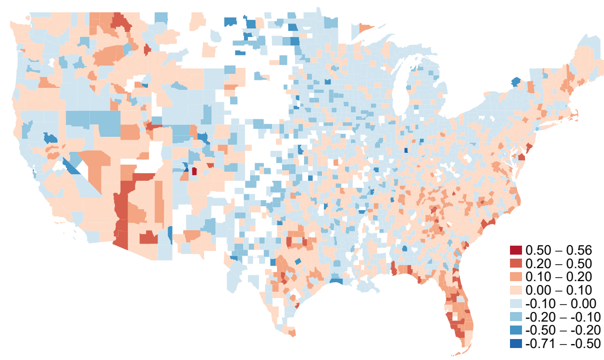
(a) Population Changes, $T = 1$



(b) Population Changes, $T = 2$



(c) Population Changes, $T = 2$ when $\mu = 100$



(d) Population Changes, $T = 2$ when using Baum-Snow and Han (2022) elasticities

Figure A8: Population changes, by county. Red counties experienced population increases and blue counties experienced population decreases. More intense colors are more positive or negative. Panel (a) shows the population changes in the first period, corresponding to February 2022. Panel (b) shows the population changes predicted by the model in the long-run. Panel (c) shows the population changes in the long-run when the model is alternatively parameterized using $\mu = 1$. Panel (d) shows the population changes in the long-run when the model is alternatively parameterized using housing supply elasticities from Baum-Snow and Han (2022), unadjusted for the fact that they are 10-year elasticities only. The same scaling is used in each panel so that the long-run can be visually compared to the short-run, and the different parameterizations can be compared to one another.

E Endogenous Elasticities

Throughout the paper, we assume that housing supply elasticities are a fixed parameter of the model. In the real world, housing supply elasticities are likely endogenous, with denser more-expensive places having less elastic housing supply (Parkhomenko, 2020). If the areas that we predict to have rent growth become less housing supply elastic and vice versa, that may mean that our baseline estimates are incorrect.

In this section, we modify the housing supply curve to have this feature. Specifically, we change the long-run housing supply curve to instead be:

$$\log H_i = \text{constant} + a_i \log r_i - \frac{1}{2}\tau(\log r_i)^2$$

where a_i is a county-specific linear term, and the quadratic term is constant across places. Rewriting this as deviations from the steady state:

$$d\log H_i = \sigma_i d\log r_i - \frac{1}{2}\tau d\log r_i^2 \tag{25}$$

where $\sigma_i = a_i - \tau \log r_{i,\text{steady state}}$. Previously, the housing supply curve was only the first term. We assume τ is positive. This housing supply equation captures the fact that the housing supply becomes less elastic when rents rise.

This means that when housing demand increases, the elasticity of the supply curve goes down and vice versa. It also gives us the equation:

$$\text{Housing Supply Elasticity}_i = a_i - \tau \log r_i$$

Based on this equation, we can estimate τ using a cross-sectional regression of the housing supply elasticities on the initial rents.[43] We present the results from that regression in Table A2. As expected, the coefficient on log rents is negative, meaning τ is a positive number.

When we replace our main housing supply equation (equation 7) with equation (25), we can no longer use simple linear algebra techniques to solve the large system of equations. However, if we define

$$\tilde{\sigma}_i = \sigma_i - \frac{1}{2}\tau d\log r_i \tag{26}$$

we can look for a fixed point between the original system of equations, and $\tilde{\sigma}_i$.

In practice, we solve the original system of equations, with the original σ_i's. Then we use the implied $d\log r_i$ that are the solution to that system, and plug them into (26). Then we use the $\tilde{\sigma}_i$ instead of the original σ_i, and solve the linear model again. We repeat until

[43] This analysis assumes that the a_i is a constant plus random variation that is i.i.d. across cities.

Table A2: Regression of Housing Supply Elasticity on Log Rents

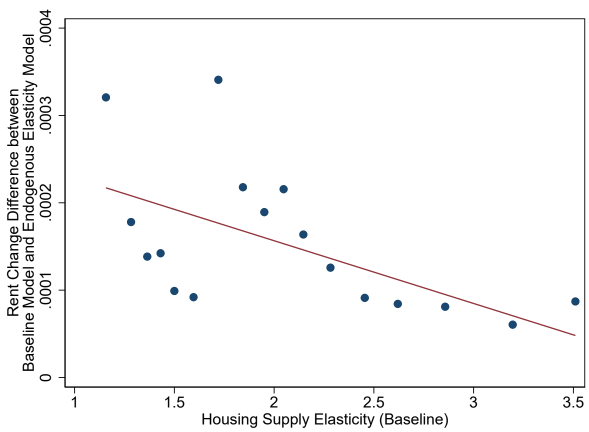
	(1) Housing Supply Elasticity
Log Rent, Feb 2020	-0.434***
	(0.0996)
Constant	5.532***
	(0.719)
Observations	502

Robust standard errors in parentheses. $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

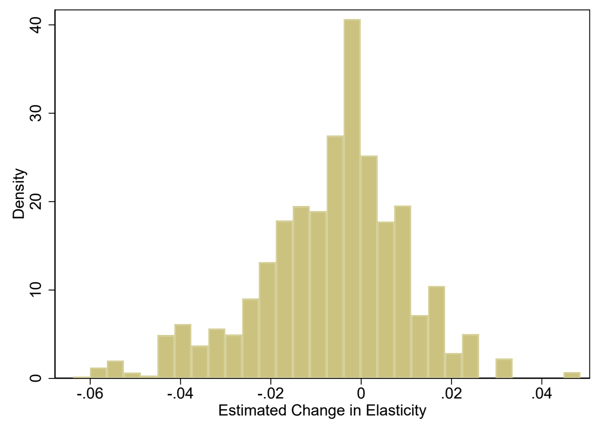
the solution converges to a fixed point in terms of $\tilde{\sigma}_i$ and $d \log r_i$.

Numerically, there is almost no difference in the solution to the model with endogenous housing supply elasticities as there was in the baseline. The housing demand channel changes from 0.01774 to 0.01780. The location demand channel changes from -0.00267 to -0.00257. While the endogenous elasticities mean that rents would rise slightly more than if they were not endogenous, the effects are small.

In Figure A9(a), we show a binned scatter plot of the difference in rents in the new model with endogenous elasticities and the rents in the baseline model with fixed elasticities, versus the baseline housing supply elasticities. Across different-elasticity counties, the new model predicts a larger rent increase for the most inelastic counties, but the difference is small for all counties. In Panel (b), we show how much the elasticities change in the new equilibrium (i.e. $-\tau d \log r_i$), weighted by population. Most people's counties see a decline in their housing supply elasticities, but the effects are fairly small across the board. This helps explain why the equilibrium is not that different in terms of rent changes, and supports our decision to endogenize the elasticities only as a robustness check and not as part of our main analysis.



(a) Rent Difference in a model with and without endogenous elasticities, plotted against baseline elasticities



(b) Distribution of Elasticity Changes

Figure A9: Endogenous elasticities