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

Greg Howard[†] Jack Liebersohn[‡] Adam Ozimek[§]

November 21, 2022

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 a different effects in the long run. We estimate that migration to more housing elastic areas will lower average rents by 0.5 percentage points, and cause a 1.8 percentage point fall in the housing component of CPI. Furthermore, the long-run effects of the increase in housing demand will be 3.7 percentage points less than the short-run effects.

JEL Codes: R31, R23, E31

Keywords: labor mobility, housing affordability, 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.

[†]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

The sudden increase in remote work caused dramatic changes in the U.S. housing market between 2020 and 2022. Recent research has documented that remote work raised the demand for housing (Behrens, Kichko and Thisse, 2021; Mondragon and Wieland, 2022; Brueckner, Kahn and Lin, 2021), flattened intracity house price gradients (Brueckner et al., 2021; Ramani and Bloom, 2021) and reallocated demand across cities (Delventhal and Parkhomenko, 2020; Mondragon and Wieland, 2022). In that period, real rents rose by eight percent and real house prices rose by over twenty percent. Short-run housing supply is highly inelastic, so it is natural that rapid demand increases caused rents and prices to rise. But in the long-run, the effects of remote work on the housing market might be quite different than during a period with little opportunity for home construction.

This paper studies the long-run effects of remote work on housing affordability and inflation. We argue that the impacts of remote work on housing affordability are likely to be different than the short-run changes. We consider two ways that remote work might change housing demand. First, demand shifts away from the central business districts of large cities, where housing is inelastically supplied. Because demand falls in areas with an inelastic housing supply and rises in areas with an elastic one, housing costs fall on average. Second, remote work increases the demand for space because people use home offices and spend more time at home (Stanton and Tiwari, 2021). This force raises the cost of housing in both the short and long run, with long-run effects depending on the average long-run housing supply elasticity.

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 the model to calculate the long-run effects of remote work in two steps. In the first step, we 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).

In the second step, we allow the housing supply elasticity to equal its historical long-run levels (Saiz, 2010; Baum-Snow and Han, 2022). We show simple formulas for long-run effect of the changing demand for where to live. We call this the *location demand* channel. Under our preferred calibration, the shift in location demand to more elastic areas will cause a 0.5 percentage point decline in rents in the long run. Our result is quantitatively similar if calculated using various parameter values used in the literature.

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 the *housing demand* channel. The model 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.[1] 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 long-run 3.3 percentage point increase in rents. Since the short-run effect is even larger, this implies a a decline of about 3.7 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 two-fifths of the short run effect. Our results also have implications for the housing component of the consumer price index (CPI). 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. We find that the effect of location demand on CPI counties is about -2 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 is about 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

[1]Other reasons include stimulus payments, low interest rates, and greater value of home consumption due to the pandemic. Mondragon and Wieland (2022) argue that at least half of the rise in housing demand comes from remote work.

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 rent increase coincides with an increase in household formation, pointing to the role of housing demand. The second stylized fact is that populations and rents grew in areas where housing supply has historically been more elastic, such as Western and Southern states. In addition, looking within urban areas, rents and populations fell in center cities and grew in the suburban and exurban ring surrounding them. Rents and populations 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 demand did not change. This means that our estimates are conservative relative to a counterfactual where housing demand continued to shift towards inelastic places, as it had done in the previous two decades (Howard and Liebersohn, 2021).

Our baseline assumption is that the location and housing demand shocks we observe in the short-run persist to the long-run. If we believe house prices are the present value of future rents, they can be used to check this assumption. While many things may have changed the aggregate price-to-rent ratio during this time period (e.g. low interest rates), we show that, in the cross-section, house prices increased one-to-one with rents. The implication of this result is that expected long-run location demand shocks are similar to short-run location demand shocks, confirming our baseline assumption.

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. 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

This work contributes to the quickly-growing literature on remote work and its economic impact. Prior to the COVID-19 pandemic, only a handful of papers considered the implications of remote work. An important early paper is Blinder (2005) who argued that improving telecommunications would make a growing share of service jobs tradeable over long distances. Ozimek (2019) argued the occupational tradeability predicted domestic remote work and not job loss. Dingel and Neiman (2020) extended this research and calculated the fraction of jobs across cities and counties that can be done remotely. They created occupational remote-ability scores which have become widely use to quantify the effects of remote work.

The rise of remote work during the pandemic led to greater research interest on the topic. The effects of remote work on the housing market have been particularly salient given the dramatic house price changes that occurred from 2020-2021.[2] Ramani and Bloom (2021) and Gupta, Mittal, Peeters and Van Nieuwerburgh (2021) show that the pandemic reduced the premium for distance to CBD within metro areas, reallocating people and housing demand from high density and more expensive places to low density places and less expensive places within metro areas. Several other papers showed that the pandemic-induced increase in remote work shifted housing demand across cities, moving demand from high productivity, high cost, high density places towards lower productivity, lower cost, lower density places (Ozimek, 2022; Althoff, Eckert, Ganapati and Walsh, 2022; Liu and Su, 2021; Brueckner et al., 2021). Brueckner et al. (2021) provides a theoretical foundation for both intracity and intercity housing market changes.

Most of the literature relating remote work to housing costs has focused on cross-sectional demand changes, particularly related to the COVID-19 pandemic. Our contribution is to study its effects on housing affordability in the long run. Understanding the implications of remote work for aggregate housing affordability requires a model of of the aggregate housing market, including the interaction of local markets through migration. Schubert (2022) shows that migration patterns are important for understanding historical house price fluctuations as well as population movements during the COVID-19 pandemic. These provide another reason we think this channel is important to quantify. While purely cross-sectional estimates can tell us how remote work changes relative house prices across cities, they are ambiguous about the effects on overall affordability. Our results show that the effects of remote work can be quite different in the long run as compared to the short run. The events of 2020-2022 cannot be taken as a guide to the future, even aside concerns about other factors affecting the housing market.

A parallel line of research studies remote work using quantitative spacial equilibrium models. These models include 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. Del-

[2]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).

venthal 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. Notably, they get a similar result to ours: when floor space is not allowed to adjust to the remote work shock in their model, residential rents are higher.[3] Given the focus of their paper on the reasons for greater remote work and the impressive multitude of quantitative features that they added to shed light on its implications for income and welfare, it is less easy to attribute the effects of this counterfactual to specific mechanisms as we do in this paper. Davis, Ghent and Gregory (2021) study the productivity effects of remote work and argue that adoption externalities led to its rapid increase. Like us, their model features both a short-run inelastic housing supply and a long-run response where supply can adjust. However, they focus on the implications for productivity and incomes rather than the effects on affordability.

Our model abstracts away from the effects of remote work on productivity or agglomeration. Instead, we take as a given that remote work raises demand for low-cost areas and show that our results are robust to considering the effects of remote work under a variety of scenarios. Our approach highlights the main forces underlying our results while being robust to alternative assumptions about the precise extent and location of remote work in the future.

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 level rent data does not cover the entire country, and imputing it from higher geographic levels would lead to inaccuracy. We think counties are 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). Ideally we would use the same measure, since we are again interested in the long-run elasticity. The Saiz (2010) elasticities have the disadvantage that they only include MSAs

[3]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.

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. The Baum-Snow and Han (2022) elasticities are estimated using a ten-year interval instead of the thirty years in Saiz (2010), and are smaller as a result. To make them comparable we multiply them by three.

The elasticities in Baum-Snow and Han (2022) are only available in certain areas, meaning that some rural areas 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 0.4. 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.[4]

In the cross-section, movements in rents and house prices during this time are highly correlated. For the quantitative exercises, we focus on rents, so as not to worry about interest rate changes and changes in expectations that may have affected home prices. At the same time, we think 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. 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. It is 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.[5]

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. Second, compared to CPI-rents it is available at a more granular level and for a larger number of locations. It is more high-frequency and less smoothed than the CPI-rents measure. 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.

[4]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.

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

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 then 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.

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). 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 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 2018 to 2022. These facts are the main aggregate and regional patterns that our model is intended to interpret. The changes from 2020 to 2022 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. We abstract away from changes in expectations that affect house prices, but 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 increase in the rate of household formation. We think that remote work increases demand for home offices (Behrens et al., 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.

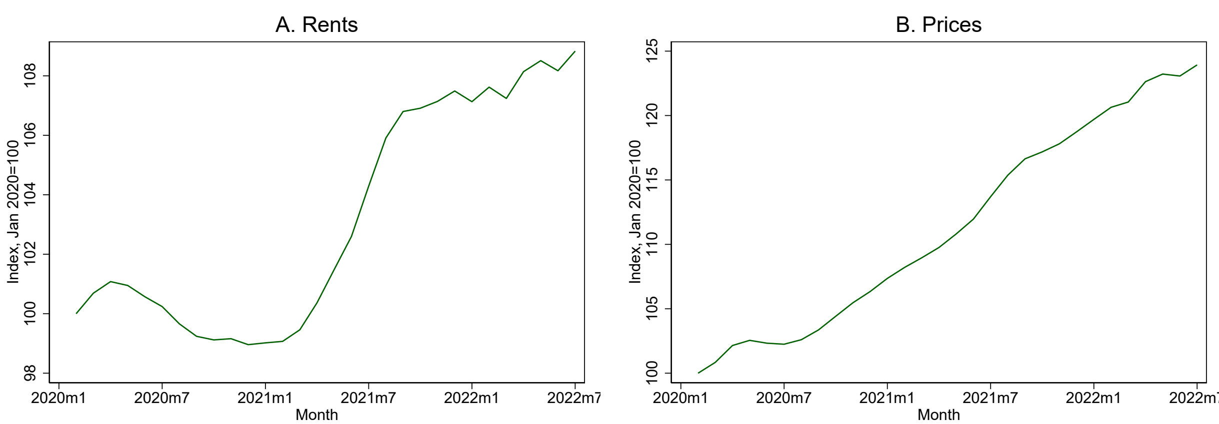
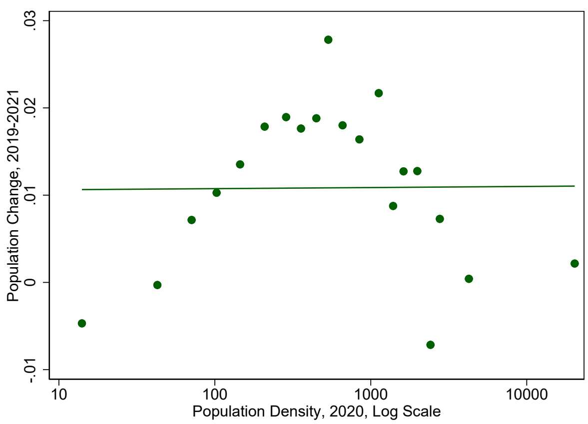


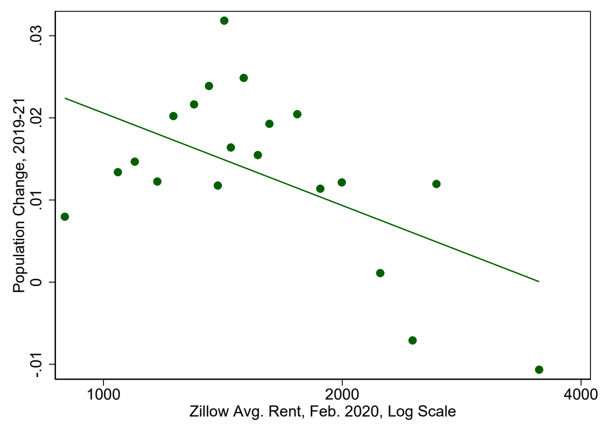
Figure 1: Panel A of shows the ZORI (Zillow Observed Rent Index) indexed to January 2020 dollars. Panel B shows the ZHVI (Zillow Home Value Index) indexed to January 2020 dollars.

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.[6]

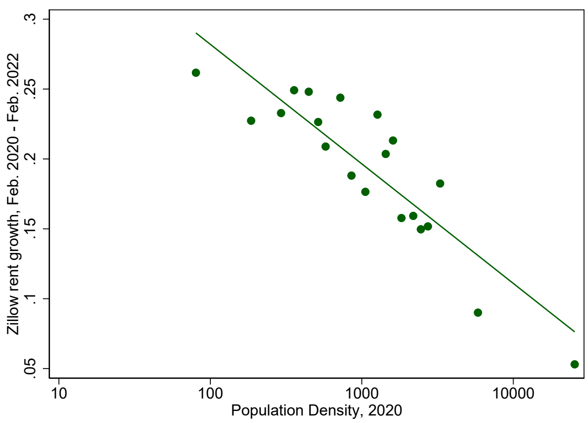
[6]We use binned scatter plots repeatedly through the paper to show data, since showing every county is too dense to read easily. A binned scatter plot sorts the data by the x-variable, and then splits them into an



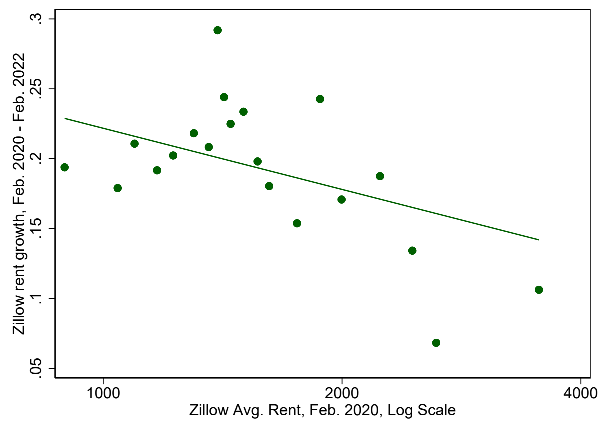
(a) Population Change vs. Density



(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.

Panels (a) and (b) provide evidence that housing demand shifted from dense central business districts ("CBD") to relatively suburban and rural areas. These figures are consistent with the evidence in several recent papers showing shifting demand away from city-centers.[7] 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).

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.

[7]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).

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.

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 fell the most 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 people's 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 (ie, location outside city center). 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, for example the shift in demand from central cities to lower-density suburban areas. Our goal is 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 by 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 of lower. In the long-run, this movement will decrease rents because housing is more elastic in more rural and cheaper areas. In addition, since supply everywhere is more elastic in the short- than the long-run, rents will fall as supply is able to respond.

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. Then, using the short-run model, we will show how to decompose the data into "shocks," and demonstrate how those shocks will effect rents in the long-run.

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 $T = 0$ or $T = 2$, 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 an i.i.d. Gumbel as is standard in the literature.[8]

$$U_{ij} = v_i(u_i, r_i) + \epsilon_{ij}$$

where u_i is a city-specific term that accounts for wages and amenities, and r_i is the rent. v is decreasing in r_i.

Per-capita housing demand is then given by

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

where x_i is a housing demand shifter, such as wages or the demand for remote workspace.[9] h_i is decreasing in r_i.

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 is local land and X is the tradable good whose price is already normalized to one. This defines a supply curve:

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

Crucially, housing supply elasticity depends on i.

[8]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-Douglass over housing consumption with housing share α and had an additive amenity term a_i, then $\log v_i = u_i - \alpha \log r_i$, where $u_i = \log w_i + a_i$.

[9]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-Douglass with housing share α, then $h_i = x_i/r_i$, where $x_i = \alpha w_i$

Local housing markets clear, and everyone lives in some city:

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

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

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

$$L_i = L \frac{(v_i)^\mu}{\sum_j (v_j)^\mu}$$

where $1/\mu$ is the scale parameter of the Gumbel distribution. So

$$\log L_i = \mu \log v_i - \tilde{u} \tag{5}$$

where $\tilde{u}$ is the log of the denominator and 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):

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

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

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

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

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

where the expectation is initial-population-weighted. These are the five key equations from Howard and Liebersohn (2021) that allow us to carry out our analysis. In order, they 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.[10]

If we have data on changes in h_i, L_i, and r_i, then we can solve the model for ϵ_i, ξ_i, and $\eta_i - d\tilde{u}$. There are four "shocks" here: 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. The last shock is the change in

[10]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.

total population.

In the short-term, $T = 1$, we assume that housing supply is fixed, and only allow a fraction ϕ of people to adjust the size or quantity of their housing in response to the shocks. 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 equations are now:

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

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

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

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

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

The exercise we wish to carry out using both the short-run equations and the long-run equations is to back out the shocks from the short-run equations and consider what will happen in the long-run if those shocks were to persist. Because of the tractability of the model, we can do this analytically.

Using equations (11)- (14), we can 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.

If those same shocks persist into the long-run, we can estimate their effect on the long-run rents. Define the Housing Demand Channel to be difference in average long-run rents, $\mathbb{E} d \log r_i$, between an equilibrium with the ϵ_i shocks and an equilibrium where the ϵ_i shocks are all set to 0.[11] Then, for the housing demand shocks ϵ, their long-run effect on aggregate

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

rents is:

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

$$= -\frac{1}{\phi(\lambda + \bar{\sigma})}\mathbb{E}d\log L_i + \frac{\lambda}{\lambda + \bar{\sigma}}\mathbb{E}d\log r_i \tag{19}$$

where equation (19) comes from plugging equation (16) into equation (18).

Intuitively, the housing demand channel is larger when the shocks to housing demand, η'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. To note, if population growth is zero, then the 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 long-run rents with the η_i shocks or with the η_i shocks being set to 0.[12] 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.[13] 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 $\mu = 0$, then the location demand channel simplifies to $Cov((\lambda+\sigma_i)^{-1}, d\log L_i)/\phi$. This because when μ is large, the location demand shocks are reflected in the rents 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.

[12] 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).

[13] When we consider the short-run, where we assume that elasticity is zero everywhere, it is clear that the location demand channel will have no effect because the covariance of a constant with anything else is zero.

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. We take these from the literature. Here, we discuss the sources of the 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.[14] We follow Howard and Liebersohn (2021) and use $\mu \to \infty$ as our benchmark value. Note that this does not mean that all households are immediately responsive to rent changes in the short run, since we will assume that only a fraction of households can move right away. 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-Douglass demand, so households spend a constant portion of their income on housing in each city, regardless of the price. At the other extreme, $\lambda = 0$ would imply unit housing demand, so housing demand does not change with price.

We use $\lambda = \frac{2}{3}$ as our benchmark value, based on an estimate from Albouy, Ehrlich and Liu (2016). In Howard and Liebersohn (2021), because $\mu \to \infty$, the results did not depend much on λ. We discuss how important the value of λ is in this setting in Section 6.1.

[14] See Table 1 of Howard and Liebersohn (2021) for a review of different values of μ and λ.

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 two-year time period that we consider. 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.[15]

5 Effect of Remote Work on Housing Demand

5.1 Demand Shock Estimates

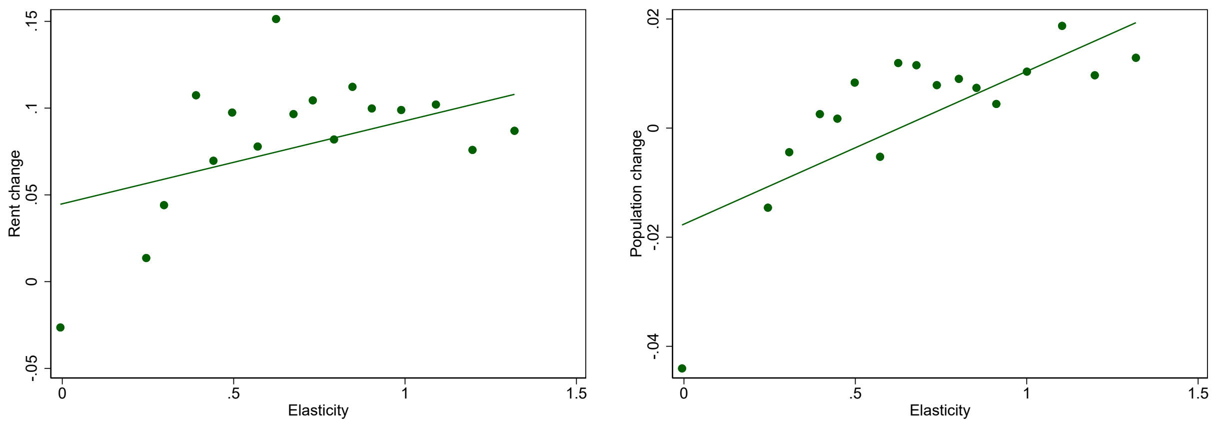
Location demand shocks η From equation (21), we learn that the covariance between housing demand shocks and the housing supply elasticity will determine the long-run effect of the demand shocks. Equation (17) shows that location demand shocks are a linear combination of rent changes and population changes. Hence what matters are the sum of these two covariances, appropriately scaled. To provide intuition for the effect of the housing demand shocks, 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 fell the most in areas where housing is the most inelastically supplied. As a result, the covariance between rent changes and housing supply elasticity is negative. For $\mu \to \infty$, local rent changes are equivalent to local housing demand shocks, and the covariance between rent changes and housing demand tell us the long run effect of

[15] An alternative lower-bound for ϕ is the share of people that did move during the time period. While we do not have data on this time period yet, about 10 percent of Americans move every year, so a reasonable lower bound might be about 20 percent.

these 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 negative 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.



(a) Rent Change vs. Elasticity

(b) Population Change vs. Elasticity

Figure 3: Binned scatter plot the relationship between real rent 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.

Housing demand ϵ From equation 19, the effect of the housing demand shock on rents depends on the average value of rent and population changes.

The rise in real rents we consider 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 4.3 (equation 16). In the long run, this will get scaled by the average housing supply elasticity as new homes are built to accommodate the shock.

5.2 Relation to Remote Work Measures

So far we have interpreted changing location demand as the result of changing remote work. This is plausible based on the timing of demand changes and based on the findings of previous papers such as Gupta et al. (2021) and Ramani and Bloom (2021). But we would also like to show direct evidence that location demand rose in areas we would expect it to using proxies for remote work developed in the literature. Specifically, we show that the rent and population changes we study are located where one where remote work is possible. To do this, we project the rent and population changes on several measures of remote work, including both vulnerability to remote work in each county itself as well as in nearby counties (to account for spillovers). Then we show the relationship between these projections and housing supply elasticities.

Our main measure is remote work feasibility measure developed by Dingel and Neiman (2020). This measure 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 since 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 an amenities measure from the USDA.

We project location demand onto remote work variables by running the following regression:

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

where WFH_i is the remote work vulnerability in location i, a_i is the level of amenities, p_i is the house price. 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.[16]

Figure 4 shows that the projection capture a lot of the variation in real rents.[17] The top

[16] Another reason distance might matter is thinking about migration (Schubert, 2022). However, in our preferred calibration of $\mu \to \infty$, we think that these spatial patterns would not emerge unless there were true differences in utility, such as from commuting.

[17] 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.

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 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, LA, 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.

The impact of the location demand shock on aggregate rents depends on the covariance between location demand and housing supply elasticity. When we use the predicted values from equation (22), the covariance is negative and qualitatively similar. The covariance between the projection and housing supply elasticity is over half the covariance between real rents and housing supply elasticity. Overall, a substantial fraction of the variation in location demand can be explained from observable variation in remote work.

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

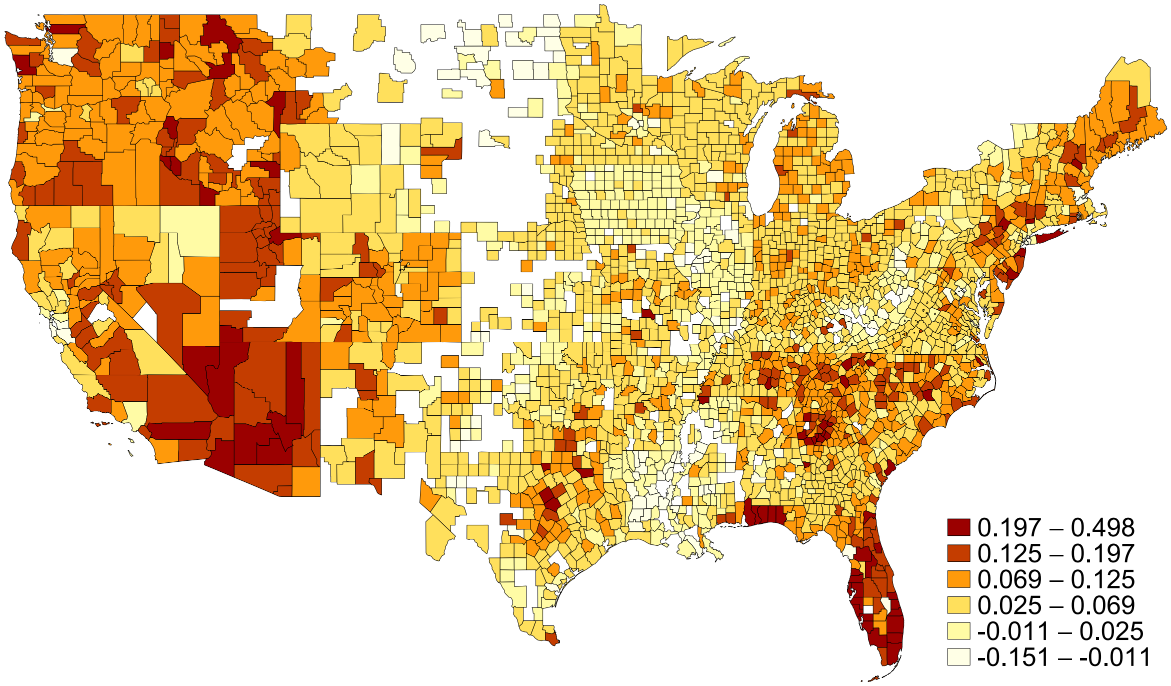
6.1 Benchmark estimates

From section 4, the long-run effect of housing demand on average rent is given by:

$$-\frac{1}{\phi(\lambda+\bar{\sigma})}\mathbb{E}d\log L_i + \frac{\lambda}{\lambda+\bar{\sigma}}\mathbb{E}d\log r_i \tag{23}$$

From the data, we know that population increased by 0.004 and the average rent increase was 0.081 log-points. Plugging these into the formula, and using our preferred calibration, the long-run effect is 0.033 log-points. Note that this is significantly smaller than the short-run effect which is simply given by $-\frac{1}{\phi\lambda}\mathbb{E}d\log L_i + \mathbb{E}d\log r_i$. This is 0.070 log-points. Hence,

A. Rent changes by County



B. Rent changes, projected onto Remote Work variables

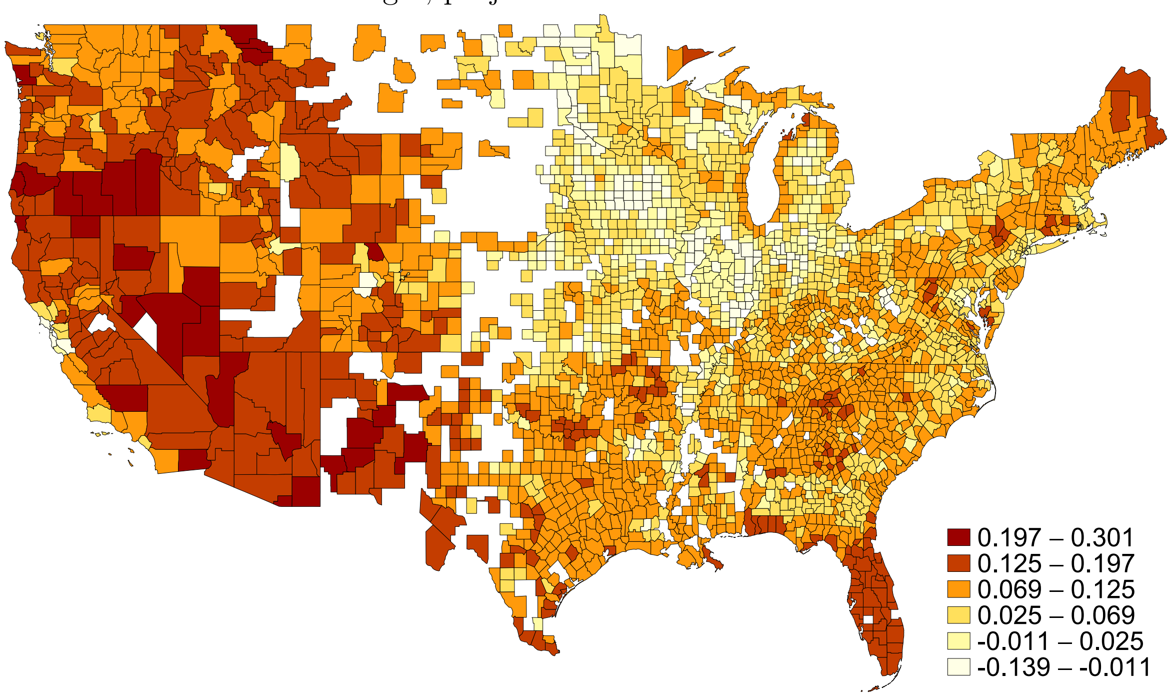


Figure 4: This figure shows real rent changes and real rent changes projected onto remote work shocks. Panel A is a chloropleth map showing the real rent change at the county level. Panel B shows the real rent change projected onto remote work measures estimated using Equation 22. The colors are on the same scale in both maps.

we expect that between the short-run and the long-run there is a decline in rents of 0.037 log-points.

As we showed in section 4, the long-run effects of location demand on average rent is given by the following equation:

$$\frac{1}{\phi}\frac{1}{\mathbb{E}\frac{\lambda+\sigma_i}{\lambda+\mu+\sigma_i}}Cov\left(\frac{1}{\mu+\lambda+\sigma_i}, d\log L_i\right) - \frac{1}{\mathbb{E}\frac{\lambda+\sigma_i}{\lambda+\mu+\sigma_i}}Cov\left(\frac{\lambda+\sigma_i}{\mu+\lambda+\sigma_i}, d\log r_i\right) \tag{24}$$

As $\mu \to \infty$, which is our preferred calibration, this has a much simpler expression:

$$-\frac{Cov(\sigma_i, d\log r_i)}{\bar{\sigma}+\lambda}$$

The numerator is about 0.0065 in the data, and the average housing supply elasticity is about 0.760. This reflects the fact that more elastic regions of the country saw bigger rent increases. So under our preferred specification of $\lambda = \frac{2}{3}$, the total effect of the location demand channel is -0.0046 log-points.

The total effect of the location demand and the housing demand channel, in the long-run, is 0.0280 log-points.

Note that when $\mu \to \infty$, the housing demand channel is the same in every location.

In the previous section, we showed that observed location and housing 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.

The location demand effects are

$$-\frac{Cov\left(\sigma_i, \hat{\eta}_i\right)}{\bar{\sigma}+\lambda}$$

where the $\hat{\eta}_i$ are the location demand shocks projected onto the remote work variables. Plugging in the numbers, the long-run effects of remote work are -0.0029 log-points from location demand. This is about 64 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.

Even though our model is one that bears similarities to many models in the literature,

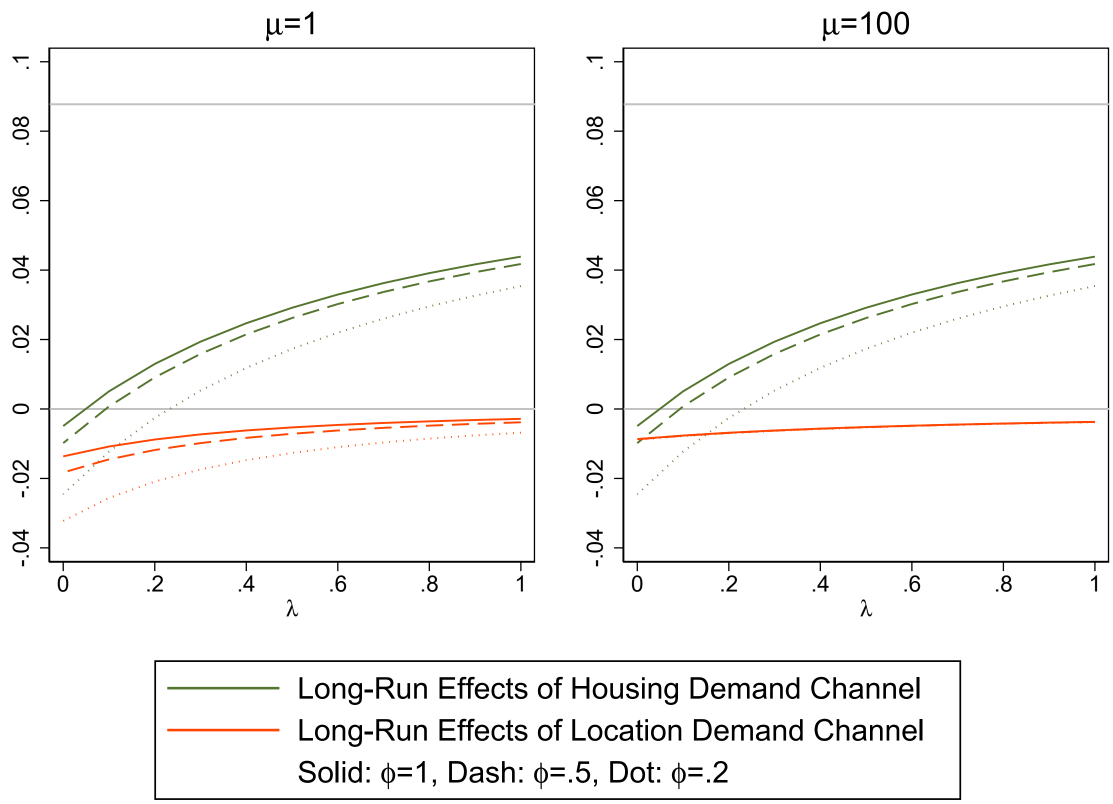


Figure 5: This figure shows the long-run average effects of housing demand and location demand on house prices. The two figures side-by-side consider different and extreme values of the location demand elasticity, μ, with $\mu \to \infty$ representing an extremely high elasticity to move in response 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.

there is not widespread agreement on the values of the parameters. In addition, our parameter ϕ is not well-estimated in the literature. Hence, we consider the robustness of our results to our choice of parameters.

In Figure 5, we show the size of the long-run effects of our two channels, for different parameter combinations that span the values used in the literature. As discussed in Howard and Liebersohn (2021), there is very little agreement on the population elasticities to rent, but luckily the effects are not very different for extreme values of $\mu = 1$ or $\mu \to \infty$ (here we show $\mu = 100$, but this is visually indistinguishable from larger values of μ). From the theory, we know that the housing demand channel does not depend on μ, so the green lines are identical in the two pictures. For the location demand channel, there are small differences because when μ is small the effect is calculated off of the change in populations and when μ

is large, the effect is calculated by the change in rents. However, since both populations and rents had relative declines in inelastic places, they tell the same story, and the quantitative interpretation is similar as well. Our conclusion is that our results do not depend much on our assumption of μ.[18]

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.[19]

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.[20]

6.2 Comparison to House Prices

A central assumption of the exercise is that the observed housing demand and location demand effects are going to persist in the long-run. There are two possible reasons to make this assumption.[21] One is to make a conditional forecast: if the shocks remain the same, how will housing affordability and population distribution change? We think this is interesting in and of itself. The other reasons is if we think the assumption is true, in which case the exercise can serve as an unconditional prediction of future housing costs. While we wish to emphasize the first use of our exercise, we nonetheless can check if observed data from house prices is consistent with the shocks being highly persistent.

[18] This is in contrast to the results in Howard and Liebersohn (2021), which depend heavily on the assumption about μ, and which is why we went to great effort to estimate μ in that paper.

[19] 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 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.

[20] In appendix A, we show that the parameters also do not affect the short-run values too much. The reader will also note that this conclusion can be derived from theory, since short-run values of the housing demand channel are a multiple of the long-run housing demand channel, and the short-run location demand channel is zero regardless of parameters. In particular, under our preferred parameterization, the short-run effect of the housing demand channel is 0.0698, and the short-run effect of the location demand channel is 0.

[21] Although this section serves as a justification of the persistence assumption, we also consider alternative assumptions in Section 6.4.

Suppose the change in house prices are the present discounted value of rents. Then the change from $T = 0$ to $T = 1$ can be log-linearly approximated by:

$$d \log p_i = w_{SR} d \log r_{i,1} + w_{LR} d \log r_{i,2} + \zeta \tag{25}$$

where w_{SR} is the weight on short-run rents, and w_{LR} is the weight on long-run rents, adding up to one. ζ is a common shock, perhaps a change in the interest rate or financing costs of mortgages, that would change house prices relative to the change in rents. We assume that ζ is common across locations.

Because of ζ, we cannot check whether the housing demand effect, which would have a common increase across all places, is persistent. But we can check the persistence of the location demand effect. Under our assumptions that η_i, the location demand shock, is perfectly persistent, and that $\mu \to \infty$, then the relative change in rents should be the same in the short-run and the long-run. Hence, the house prices should increase one-for-one with rents.

We can check this by running a regression of house price changes on rent changes. To do this, we run a regression of house price changes from February 2020 to February 2022, using the Zillow Housing Value Index, on rent changes over the time period.[22] If the long-run η is the short-run η plus noise, then we would expect the coefficient of this regressiont to be 1. In Table 1 Column (1), we show that the coefficient is about 0.8, which would suggest that the shocks are not fully persistent and that places with relatively high short-run rents will not have as large of long-run rents.

One reason for the coefficient to be less than 1 could be measurement error in the short-run rents. To check this, we use another data source for the increase in rents as an instrument. We use data from Costar, which also produces a county rent index, although it only reflects commercial properties. Nonetheless, it should be correlated with the true increase in rents, but not the measurement error in Zillow. When we perform two-stage least squares using the Costar Rent Growth as an instrument (column 2), we find a coefficient very close to 1, suggesting the parts of rent growth that are not measurement error are very persistent. Controlling for elasticity, in case there is a differential trend in how the location demand evolves by elasticity, does not effect the coefficient. And furthermore, the coefficient on elasticity is very close to zero.

Based on the house price data, we conclude that it is reasonable to expect the η's, i.e. the location demand shocks, that we estimate to persist into the long-run. Of course, our

[22]We do not use the rent data we imputed from house prices because that would bias this regression. We just use the change in the ZORI index for counties which ZORI is created. This reduces our sample size to a bit under 500 counties, but this is a large majority of the population.

Table 1: House Price Increases Compared to Rents

	(1) House Price Growth	(2) House Price Growth	(3) House Price Growth
Rent Growth	0.796***	1.033***	1.033***
	(0.0579)	(0.0696)	(0.0777)
Housing Supply Elasticity			-0.00212
			(0.0416)
Constant	0.141***	0.118***	0.118***
	(0.00592)	(0.00781)	(0.0100)
Observations	490	483	483
First-stage F		363.0	309.2
Instrument		Costar Rent Growth	Costar Rent Growth

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

model is able to accommodate thinking about alternatives to this assumption as well, which we consider in Section 6.4.

6.3 Cross-Sectional Effects

While the main focus of the paper is on the aggregate effect of remote work on rents, there is significant heterogeneity in the effects that remote work will have in the long-run.

Under our preferred parameterization, the cross-sectional effects of remote work are the same in the long-run and the short run, since as $\mu \to \infty$, the relative rent changes between any two locations is given by the difference between their location demand shocks. So even though the location demand shocks have a small negative aggregate effect, in some places, they will have quite positive effects, and on some, quite negative.

One subgroup of particular interest is the metropolitan areas in which the CPI is measured. Because it is only meant to cover urban areas, the effect on CPI measure of rents, even in the long-run,[23] is not the same as the national aggregate.

The effect on CPI of location demand is given by:

$$\text{Long-run location demand channel}_{CPI} = -\frac{Cov(d\log r_i, \sigma_i)}{\bar{\sigma} + \lambda} + \overline{d\log r_{CPI}} - \overline{d\log r_i}$$

Since the difference in rents is approximately .0137, that means the long-run effect of location demand on CPI-measured counties is -0.018.

While the main focus of the paper is on the effect that remote work will have on rents, we show in this section that the short- and long-run effects of remote work on populations are

[23] In the short run, CPI lags other measures of rents such as the Zillow rents.

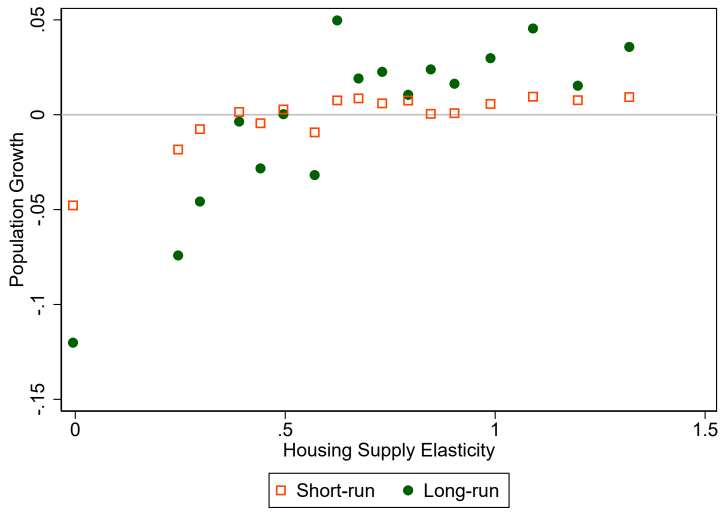


Figure 6: A binned scatter plot of the short- and long-run population changes due to housing and location demand shocks, by housing supply elasticity

also quite different. The reason for this is that in the long-run, the greater ability of people to move, and the greater ability of housing supply to adjust, especially in the places where it is now in more demand, will mean way more people end up moving to housing supply elastic parts of the country.

When we look at populations, there are also interesting long-run effects of remote work. In the long-run, housing supply in the places where demand increased will grow, and people will move into those areas. The people that we constrained not to move will also be able to move in the long-run. In the long-run, the effect of the housing demand and location demand shocks are,

$$d \log L_i = (\sigma_i + \lambda)(\eta_i - d\tilde{u}) - \epsilon_i \tag{26}$$

where $d\tilde{u}$ is a constant that makes it so that $\mathbb{E} d \log L_i = 0$. While in the short-run,

$$d \log L_i = \lambda\phi(\eta_i - d\tilde{u}) - \phi\epsilon_i \tag{27}$$

Note that the $d\tilde{u}$ are different in the short- and long-run. So in general, the places that grew in the short-run will also grow in the long-run, but even more so if they have high housing supply elasticities. We plot this in Figure 6. The most-inelastic counties have already lost 5 percent of their population to the housing demand and location demand shocks identified by the model. But in the long-run, they will lose more than twice that amount.

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 0.76 housing supply elasticity, had a Zillow home value index of \$309,986, and had a population density of 1638 people per square mile. The short-run effect was to change those numbers to .76, \$308,171, and 1598 people per square mile, respectively. But the long-run effect of these shocks is that people will move to places that had 0.77 elasticity, \$304,836 Zillow home value index, and 1511 people per square mile in 2019.[24] So, the long-run effect on population movements is that the average American lives in a county that is 1 percent more elastic, 1.7 percent cheaper, and 7.8 percent less dense in 2019. This is in addition to the fact that we expect housing costs to increase by 2.8 percentage points on net, and that outmigrants will affect the density of the most dense places.

6.4 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. Of course, 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? 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?

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

[24] 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 it is a helpful summary statistic for understanding the movement of population.

Table 2: Alternative Scenarios

Scenario	(1) Housing Demand Channel	(2) Location Demand Channel	(3) Total	(4) Total on CPI
Baseline	0.033	-0.0046	0.028	0.014
60% Housing Demand	0.020	-0.0046	0.015	0.001
700% Location Demand	0.033	-0.032	0.001	-0.096
200% Amenities	0.033	-0.0063	0.027	0.009

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

So 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, e.g. 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 0.0046 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 0.033 times x percent. So if you think only 14 percent is due to remote work, you would believe that the net effect is 14 percent times 0.033, 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 0.196, plus the location demand channel, for a net effect of 0.0150.

6.4.2 Expansion of remote work

Our location demand channel also scales linearly with the size of the shock. So 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, and so the location demand channel would be 0.032, which would make the net effect basically zero. In this scenario, the difference between CPI rents and aggregate rents is also amplified by a factor of 7.

6.4.3 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 high-amenity low-rent places.

The coefficient on amenities was 0.0104 in regression (17). And the coefficient on amenities times initial log house prices was -0.0174.[25] If we assume those both double, the additional effect on average rents would be

$$-0.0104\frac{Cov(\text{amenities}, \sigma_i)}{\bar{\sigma} + \lambda} + 0.0174\frac{Cov(\text{amenities} \times \log p_i, \sigma_i)}{\bar{\sigma} + \lambda}$$

which is -0.0017, which when added to the location demand channel adds up to -0.0063.

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.

[25] We demean house prices so that we can still interpret the first coefficient as the effect at an average house price. For a sense of what these numbers mean, the population-weighted standard deviation of the amenity index is 3.28 and of log house prices is 0.59.

References

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.

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.

Glaeser, Edward L and Joseph Gyourko, "Housing dynamics," 2006.

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.

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.

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.

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.

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.

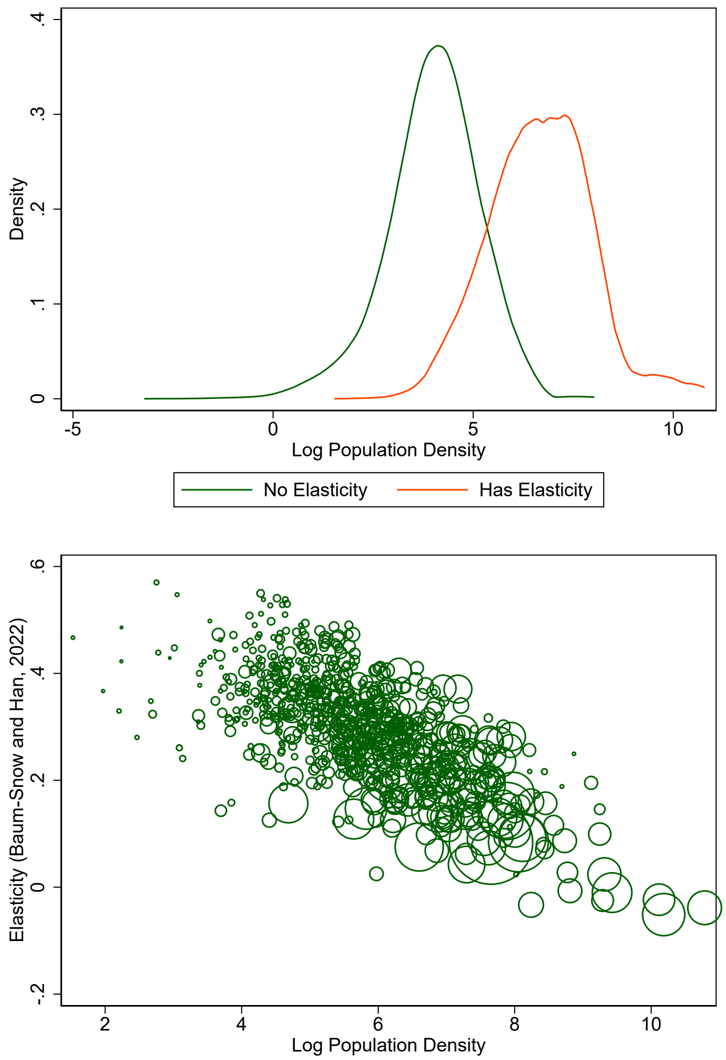


Figure A1: Upper panel: Log density of counties, with and without Baum-Snow and Han (2022) elasticities. Lower panel: Scatter plot with the relationship between population density and housing supply elasticity.

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.

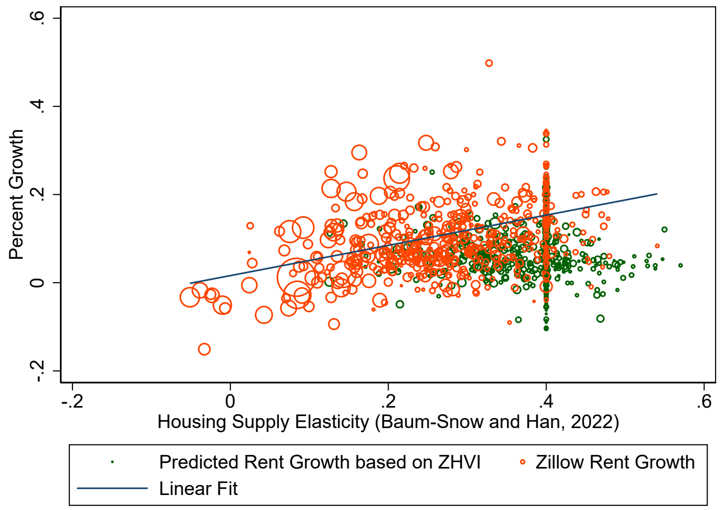


Figure A2: Rent Growth, 2020-2022

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.

Table A1: Projecting Rent Changes onto Remote Work variables

	(1) Rent Changes, Feb 2020-Feb 2022
Amenity Index	0.0104***
	(0.000808)
Log House Price, Feb 2000	0.0557***
	(0.00900)
Amenity Index × Log House Price, Feb 2000	-0.0174***
	(0.000668)
Work From Home Share	0.102
	(0.0601)
Work From Home Share within 25 miles	-0.295***
	(0.0837)
Relative House Price within 25 miles	-0.124
	(0.0778)
Work From Home Share within 25 miles × Relative House Price within 25 miles	0.185
	(0.198)
Work From Home Share within 50 miles	0.378***
	(0.0878)
Relative House Price within 50 miles	0.160*
	(0.0669)
Work From Home Share within 50 miles × Relative House Price within 50 miles	-0.242
	(0.164)
Work From Home Share within 100 miles	-0.236*
	(0.0997)
Relative House Price within 100 miles	0.252***
	(0.0695)
Work From Home Share within 100 miles × Relative House Price within 100 miles	-0.770***
	(0.169)
Work From Home Share within 250 miles	-0.735***
	(0.158)
Relative House Price within 250 miles	-0.177
	(0.0987)
Work From Home Share within 250 miles × Relative House Price within 250 miles	0.407
	(0.241)
Work From Home Share within 500 miles	-0.584***
	(0.170)
Relative House Price within 500 miles	0.694***
	(0.117)
Work From Home Share within 500 miles × Relative House Price within 500 miles	-1.858***
	(0.292)
Constant	0.623***
	(0.0578)
Observations	2716
R^2	0.382

Standard errors in parentheses. Regression weighted by county population in 2019. $^{*}p < .05$, $^{*}*p < .01$, $^{*}**p < .001$.

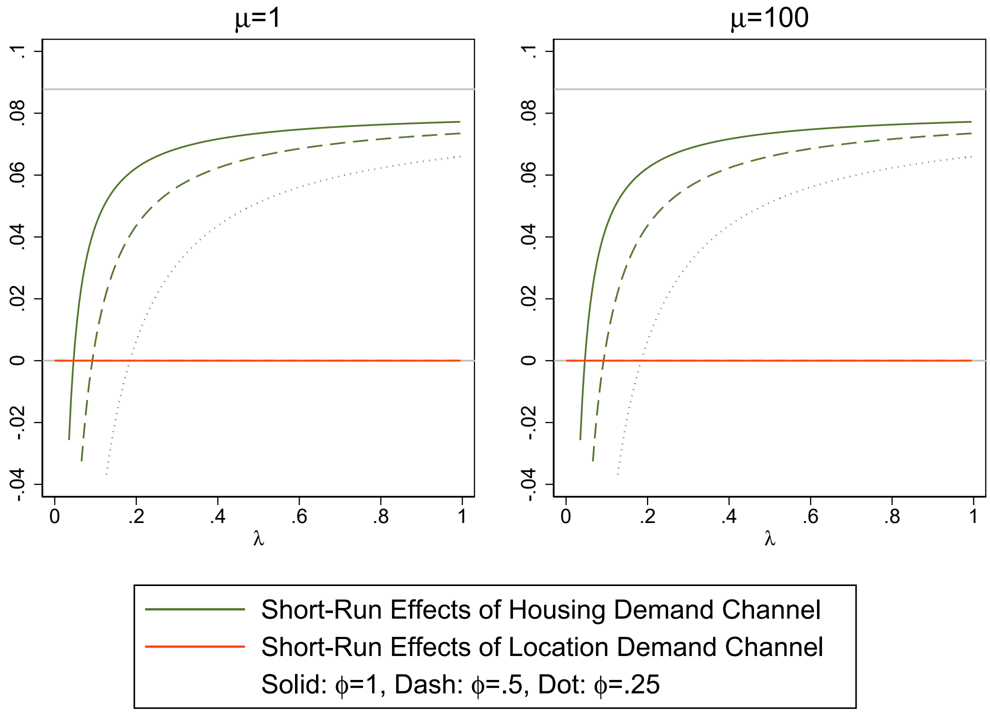


Figure A3: Parameter Sensitivity, short-run effects

In Figure A3, 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.

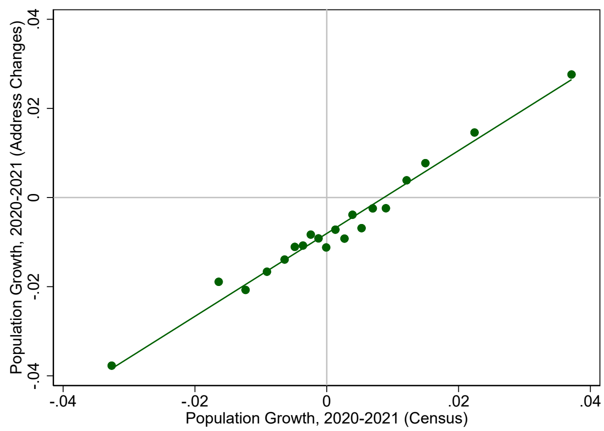


Figure A4: A binned scatter plot of population growth implied by address changes versus Census-estimated population growth

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. So 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 binscatter plot of the two measures of population growth to show that their relationship is linear.