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Stuck at Home: Housing Demand During the COVID-19 Pandemic

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Keywords

COVID-19, Pandemic, Stay at Home, Housing, House Prices, Consumption, Mortgage Interest Rates, Unemployment, Fiscal Stimulus

JEL Classification

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1. Introduction

Why have US house prices grown so rapidly during the COVID-19 pandemic? Dramatic increases in uncertainty about health, the macroeconomy, and social circumstances might have predicted a sharp downturn in housing markets.[1] But house prices increased by around 10 percent in real terms in 2020, and rose by 15 percent in the year to July 2021 (see Figure 1). Housing demand is likely to have been affected by a range of pandemic-related factors. While unemployment increased, real borrowing costs declined and the US government provided substantial fiscal stimulus.[2] Household activities and consumption patterns also changed dramatically. In particular, households spent much more of their time and money at home. In this paper, we argue that the greater utilization of housing was associated with a significant increase in the demand for and valuation of houses. In particular, we study the extent to which stay-at-home shocks explain the rise in house prices during the pandemic.

Our paper presents both empirical evidence and quantitative modelling analysis that show that the shift towards at-home activity was associated with a significant increase in house prices. First, we document large and persistent shifts towards household time spent at home and expenditures on at-home consumption during the pandemic. We then provide cross-sectional evidence that counties with larger increases in time spent at home also experienced faster house price growth. Second, we build a heterogeneous agent model with general equilibrium in housing markets to study the quantitative importance of stay-at-home shocks during the pandemic. In the model, households consume goods away-from-home, goods at-home, and housing services. We model a stay-at-home shock as a change in consumption preferences that is consistent with the observed shift towards at-home consumption during the pandemic. Since at-home goods and housing services are consumed together, the shock also raises the demand for housing and increases house prices in equilibrium. In a series of dynamic pandemic experiments, we find that stay-at-home shocks account for nearly half of the overall rise in house prices during 2020.

We begin by studying the changes in consumption patterns and time-use during the pandemic. Using household-level micro-data from the Consumer Expenditure Survey (CEX), we show that at-home consumption expenditure rose significantly in 2020. The share of food expenditure on food consumed at home rose from around 65 percent to around 70 percent during 2020. We construct a measure of non-durable goods and services, and we show that the away-from-home share of non-durables fell by 4 percent, while the at-home consumption and housing services shares rose by around 2 percent each.[3] These changes in consumption patterns are also reflected in changes in the time that households spent at home and away from home. Drawing on

[1]For example, the Mortgage Bankers Association cited macroeconomic uncertainty as the main reason for a sharp tightening of mortgage credit in March and April 2020. See https://www.mba.org/2020-press-releases/may/mortgage-credit-availability-decreased-in-april.

[2]On the variety of fiscal policies enacted and their various effects see, for example, Carroll et al. (2020), Devereux et al. (2020), Faria-e-Castro (2021), and Lacey, Massad, and Utz (2021).

[3]While food expenditures reported in the CEX are explicitly categorized into at-home and away-from-home consumption, other expenditures are not. We show that the changes in our measures of non-durable expenditure shares are robust to different assumptions about which goods and services are consumed away-from-home or at-home. See Section 2.2 and Appendix A for details.

measures of household mobility during the pandemic from Google Mobility Reports, we show that nationally, households spent around 10 percent more time at home during 2020.

We then provide cross-sectional regression evidence that more time spent at home is associated with greater housing demand. Using monthly county-level data from 2020, we regress real house price growth on time spent at home as well as the number of visitors to retail and recreational locations. In addition to controlling for a range of potentially confounding factors, we also make use of a plausibly exogenous instrument for changes in household mobility. We construct a shift-share instrument by combining the county-level share of jobs that can be performed at home (Dingel and Neiman, 2020) with state-level measures of pandemic intensity (Hale et al., 2021). Both our OLS and 2SLS results suggest a strong positive relationship between household mobility and house price growth during the pandemic.

Next, we build a structural model of the housing market to rationalize our empirical evidence and quantitatively assess the overall contribution of stay-at-home and other macroeconomic shocks to house price growth during the pandemic. Our model features heterogeneous households that consume goods away from home, goods at home, as well as housing services. We assume that at-home goods and housing services are consumed as part of a home bundle, while away-from-home goods are imperfect substitutes for this bundle.[4] We model stay-at-home shocks during the pandemic as a shift in preferences towards consumption of the home bundle, which in-turn causes an increase in demand for both at-home goods consumption as well housing services.[5] Housing may either be rented or purchased with the help of mortgage financing. Households are subject to both idiosyncratic income shocks and age-dependent employment shocks. Homeowners are also limited in how much they can borrow, which affects their ability to smooth consumption over time. We calibrate the model to match pre-pandemic statistics on unemployment, income, homeownership, wealth, and consumption expenditure shares.

We model the pandemic as a collection of four shocks that hit the economy in 2020 and 2021 and study the dynamics of housing demand over this period. In addition to the preference shocks that induce households to consume more at home, we include a negative shock to mortgage interest rates, a spike in unemployment, and large fiscal transfers in the form of stimulus checks and expanded unemployment benefits. Our calibrated pandemic shocks are sufficient for our model to match the excess rate of house price growth observed in 2020. We use the model to decompose the increase in house prices into contributions from each of the shocks, and to shed light on the underlying sources of rise in housing demand. The model suggests that stay-at-home shocks to preferences explain nearly half of the overall increase in house prices in 2020. Declining mortgage interest rates explain a little over a third of house price increase, while unemployment shocks and fiscal stimulus have relatively small effects on house prices. We show that much of increase in housing demand is driven by first-time home buyers, with some additional effect due

[4]Our model is related to the macroeconomic literature on home-production. See, for example, McGrattan, Rogerson, and Wright (1997), Rogerson and Wallenius (2016), Aguiar and Hurst (2007), and Nevo and Wong (2019).

[5]This aggregate preference shock is consistent with a view of the pandemic in which households stay home to avoid falling ill to the virus, even in the absence of government directions to do so (see, for example, Chetty et al., 2020).

to more existing homeowners upsizing and fewer existing homeowners downsizing their housing stocks. Finally, our model suggests that most of the underlying increase in housing demand comes from young households that would like to become homeowners. However, the general equilibrium rise in house prices crowds out many of these would-be buyers, which results in an overall decline in homeownership rates for the young during the pandemic. Overall, we find that the forces leading households to spend more of their time and money at home account for the bulk of the increase in housing demand observed during the pandemic.

1.1. Related literature

A growing literature explores the impact of COVID-19 on real estate markets. On the empirical side, several papers document that within cities housing demand shifted away from urban cores toward lower-density suburban areas during the pandemic (Gupta et al., 2021; Liu and Su, 2021; Ramani and Bloom, 2021; Guglielminetti et al., 2021). Both Gupta et al. (2021) and Liu and Su (2021) show that house prices and rents grew faster in locations further from city centers. In addition, these changes in relative prices were larger in cities that had a higher fraction of jobs that could be done from home (WFH). Delventhal, Kwon, and Parkhomenko (2020) and Davis, Ghent, and Gregory (2021) use spatial equilibrium models of internal city structure and worker location choice to study the increase in WFH during the pandemic. Consistent with the intra-city empirical evidence, these models generate declining demand for inner-city housing relative to the rising demand for houses further from the city center.

Our paper also contributes to an understanding of the importance of stay-at-home shocks in driving housing market dynamics during the pandemic. However, we make two points of departure from the previous literature. First, we do not model the impact of stay-at-home shocks on housing demand as explicitly arising from an increase in WFH. Rather, we model the effect of stay-at-home shocks through the complementarity between at-home consumption and housing services. Our motivation for exploring this channel is the large and persistent shift towards the consumption of goods and services at home during the pandemic, which we document in Section 2. This novel housing demand channel rationalizes our empirical finding that locations where households spent more time at home and less time at retail and recreation establishments experienced faster house price growth. Second, we study the aggregate effects of pandemic shocks on housing demand, rather than the reallocation of housing demand across space within a given market. Our focus on aggregate dynamics is motivated by the fact that the increase in house prices has been broad-based across US regions, and has occurred against the backdrop of other important aggregate shocks such as rising unemployment, falling real mortgage rates, and generous fiscal support. We use our quantitative model of the housing market to disentangle the effect of stay-at-home shocks on housing demand from the effects of these other aggregate factors.

Our paper also relates to the much larger literature that uses quantitative macroeconomic models to study the effects of COVID-19 and the associated government policy responses. As in our model, the previous literature variously studies the effect of unemployment shocks (Carroll et al., 2020; Fang, Nie, and Xie, 2020), sectoral demand or supply shocks (Danieli and Olmstead-Rumsey, 2021; Faria-e-Castro, 2021; Guerrieri et al., 2021; Graham and Ozbilgin, 2021), and fiscal policies regarding unemployment insurance and transfer payments (Bayer et al., 2020; Carroll et al., 2020; Mitman and Rabinovich, 2020; Fang, Nie, and Xie, 2020; Faria-e-Castro, 2021; Kaplan, Moll, and Violante, 2020b). While several of these papers build heterogeneous agents models to understand the role of the wealth distribution in the pandemic (for example, Carroll et al., 2020; Nakajima, 2020; Kaplan, Moll, and Violante, 2020b), we specifically focus on the effects of pandemic shocks in a heterogeneous agent model with housing. We then study a novel sectoral demand (i.e. stay-at-home) shock which shifts consumption towards at-home goods while simultaneously increasing the demand for housing services. Our primary contribution is to show that these stay-at-home shocks account for nearly half of the overall increase in housing demand during the pandemic.

Finally, our quantitative analysis builds on a large and growing literature that embeds illiquid housing assets and mortgage finance decisions in incomplete markets models to study the interaction between aggregate fluctuations and the housing market (see, for example, Iacoviello and Pavan, 2013; Garriga and Hedlund, 2020; Kaplan, Mitman, and Violante, 2020a; Guren, Krishnamurthy, and McQuade, 2021; Kinnerud, 2021). We extend the standard environment typically studied in these models by assuming households have preferences over a composite of away-from-home and at-home non-durable consumption goods, as well as housing services. Additionally, we incorporate life-cycle unemployment fluctuations, which do not typically feature in the existing literature. These additional features allow us to study the effects of changes in the composition of consumption, shocks to unemployment, and fiscal stimulus measures during the pandemic on outcomes in the housing market.

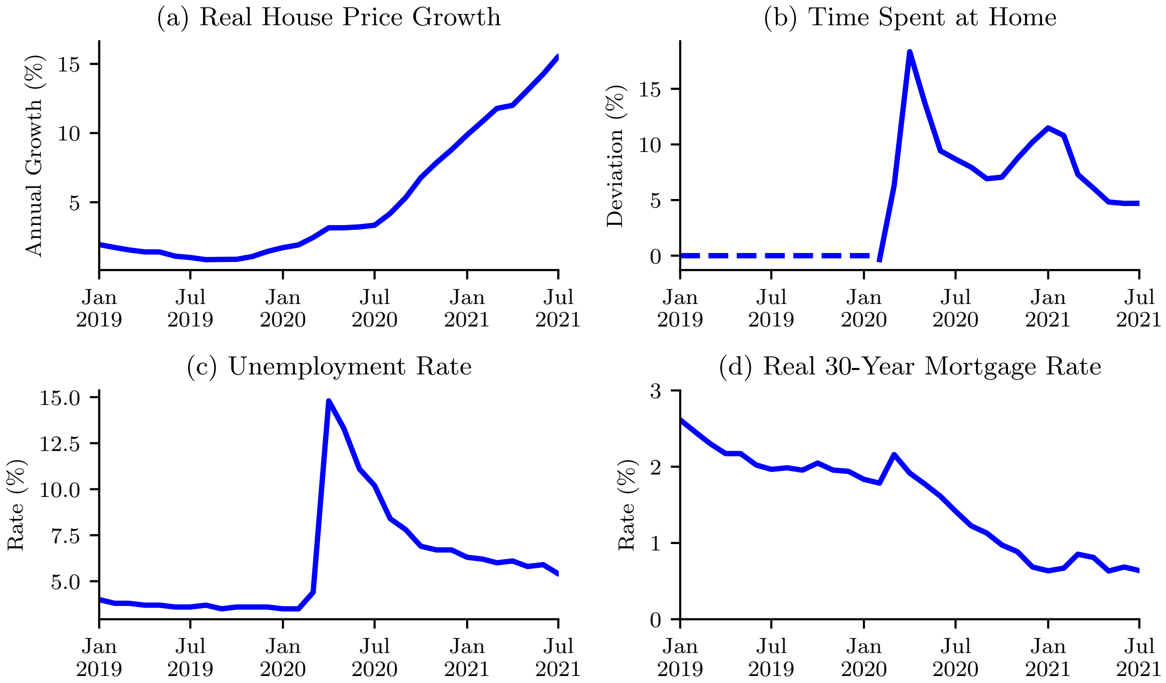
2. Motivating Evidence

In this section, we document two related patterns in the data over the course of the pandemic. First, there was a significant acceleration of house price growth in the US. Second, households spent significantly more time at home and shifted expenditures towards at-home consumption of goods and services. We then provide cross-sectional evidence that more time spent at home is associated with faster house price growth.

2.1. Aggregate trends during the pandemic

Figure 1 depicts the evolution of four key macroeconomic aggregates before and during the pandemic. Panel (a) shows the annual growth rate of the S&P/Case-Shiller national house price index adjusted for CPI inflation. Real house price growth accelerated sharply during 2020. While the growth rate in the year to July 2019 was just 2 percent, prices grew by 5 percent from July 2019 to July 2020 and by 15 percent from July 2020 to July 2021. Note that the S&P/Case-Shiller index is a repeat sales price index, so the changes in prices reported in panel (a) are adjusted for any differences in the composition of houses sold over the course of the pandemic. Panels (b)–(d) depict the evolution of macroeconomic aggregates that are

Figure 1: Evolution of Macroeconomic Aggregates During the Pandemic



Notes: Real house price growth (panel a) is the 12-month growth rate in the S&P/Case-Shiller U.S. National Home Price Index minus annual core CPI inflation. Mobility away from home (panel b) is time spent away from home from Google Mobility Reports. The real 30-year mortgage rate (panel d) is the 30-Year Fixed Rate Mortgage Average in the United States from the Freddie Mac Primary Mortgage Market Survey minus the 30-year breakeven rate derived from 30-Year Treasury Constant Maturity Securities and 30-Year Treasury Inflation-Indexed Constant Maturity Securities.

Source: Authors' calculations using data from FRED and the Opportunity Insights Economic Tracker.

likely to be related to house prices over this period. Panel (b) shows changes in the time that households spent at home, from Google Mobility Reports data.[6] Early in the pandemic, time spent at home increased by more than 15 percent. Households continued to spend more time at home throughout 2020 and 2021, and as at July 2021 this measure remained 5 percent above its pre-pandemic level. Panel (c) documents the exceptionally sharp increase in unemployment during 2020. The unemployment rate quickly increased to nearly 15 percent, and then gradually declined to 5.4 percent by July 2021. Finally, panel (d) shows that real 30-year fixed mortgage interest rates declined by a little over 1 percentage point from 2019 to 2021.[7]

[6] Google uses anonymized GPS information gathered from personal cell phones to track where households have spent time over the course of the pandemic. Changes in various measures of household mobility are computed by comparing to baseline mobility measured during the five-week period from January 3 to February 6, 2020. For more information see: https://www.google.com/covid19/mobility/.

[7] To compute real interest rates at the 30-year horizon, we use expected 30-year inflation rates by combining information from nominal 30-year Treasury constant maturity securities and inflation-indexed 30-year Treasury constant maturity securities.

2.2. The rise in at-home consumption

While much more time was spent at home during the pandemic, households also shifted their consumption expenditure towards at-home goods and services. To measure the magnitude of this shift, we study household consumption patterns reported in the Consumer Expenditure Survey (CEX), a monthly survey of U.S. household expenditures. In each survey, the CEX questions a rotating panel of households about their consumption over the previous quarter across a number of detailed consumption categories. Additionally, the survey reports a range of demographic information about the panelists, including whether they own or rent their home.

We construct two measures of expenditure on non-durable goods and services consumed at home and away from home. First, we use the CEX categories for food consumed at home and food consumed away from home. Although this measure is limited to food expenditures only, it has the benefit of being explicitly separated into consumption at home and away from home.[8] Second, we construct a measure of non-durable consumption expenditure that includes food, apparel, personal care, non-durable transportation, non-durable entertainment, housing services, alcohol, tobacco, education, and health.[9] This measure is similar to the one used by Aguiar and Hurst (2013), but expanded to include education and healthcare spending. We then divide the non-durable consumption categories into those that are plausibly consumed at home and away from home. In our baseline definition, we assume that consumption at home consists of food at home, apparel, non-durable entertainment, and personal care. We assume that consumption away from home includes food away from home, alcohol, tobacco, transportation, health, education, and fees and admissions. In Appendix A we show that all of our results are robust to alternative definitions of consumption at home and away from home. We then separate housing services into its own category of consumption. Finally, all of our statistics are computed using the core weights provided by the Consumer Expenditure Survey.

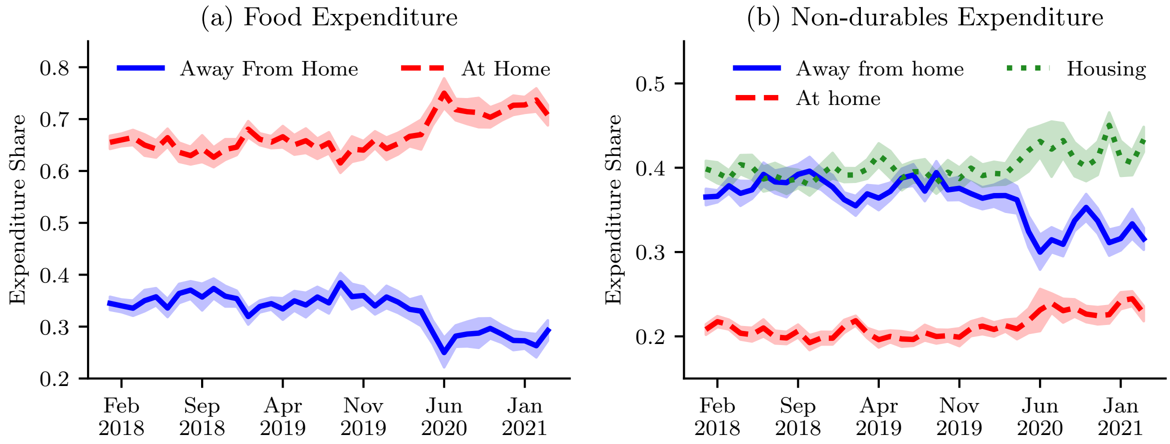
Figure 2 shows median household consumption expenditure shares prior to and during the pandemic. Both of our measures of consumption show that households shifted expenditure towards consumption at home, and out of categories consumed away from home. Panel (a) shows that while the expenditure share on food at home had been stable at around 65 percent in the years prior to the pandemic, it increased by 5 percent in 2020. Panel (b) reports the expenditure share of non-durables on consumption at home, away from home, and on housing services. The three non-durable consumption shares had also been relatively stable prior to the pandemic at 20 percent, 38 percent, and 39 percent respectively. From 2019 to 2020, the at-home share rose by 1.9 percent, the housing services share rose by 2.0 percent, while the away-from-home share of consumption fell by 3.9 percent.

In Appendix A we show that these results are robust to alternative definitions of away-from-home and at-home consumption. In Figure A.1 spending on health, education, alcohol,

[8]Using the CEX Blundell, Pistaferri, and Preston (2008) show that food consumption is a good predictor of overall non-durable consumption.

[9]Our measure excludes some components of expenditure in the CEX, including automobile purchases, home maintenance and services, mortgage interest payments, insurance, reading, cash contributions to people or organizations outside the household, and some other small categories.

Figure 2: Median Consumption Expenditure Shares



Notes: Median consumption expenditure shares for (a) food only, and (b) non-durables and housing services. Shaded regions show 95% confidence intervals for the median expenditure shares, computed via bootstrapping. In panel (b) spending on alcohol, tobacco, transportation, health, education, and fees and admissions is allocated to spending away from home. Household weights used to compute median shares, with weights provided by the CEX.

Source: Authors' calculations using data from the CEX.

and tobacco are allocated to consumption at home. In that case, the median non-durables share spent at home rises by 2.7 percent and the share spent away from home falls by 4.3 percent in 2020. Since these changes in consumption shares are similar to those reported in Figure 2, it must be that the shifts in consumption are largely associated with a few key categories, such as food, fees and admissions (which includes recreation items, such as movie and concert tickets), and transport. Figure A.2 reports aggregate consumption shares, which exhibit very similar patterns to the median consumption shares.

Finally, Figure A.3 in Appendix A shows consumption shares separately for homeowners and renters using our baseline definition of at-home and away-from-home consumption. Although the levels of the expenditures shares are different for homeowners and renters, we find little difference between the changes in their respective consumption shares during the pandemic. For homeowners, the at-home consumption share rises by 2 percent, the away-from-home share falls by 4 percent, and the housing services share rises by 2.1 percent. For renters, the at-home consumption share rises by 1.6 percent, the away-from-home share falls by 4 percent, and the housing services share rises by 2.3 percent. This result suggests changes in consumption shares are not driven by differences in the evolution of housing costs for owners and renters during the pandemic.

2.3. Time at home and house prices

In this section we investigate whether more time spent at home during the pandemic was associated with changes in demand for housing, as observed in house price growth. We use cross-sectional variation in county-level data and find that locations with greater increases in time spent home or larger decreases visits to retail or recreation establishments also experienced larger increases in house prices. That is, more time and money spent at home appears to be associated with larger increases in housing demand.

Our data on household mobility come from the Google Mobility Reports data. We use two measures of household mobility at the county-level: time spent at home, and the number of visits to retail and recreation locations.[10] The first of these directly measures the extent to which households are spending more time at home during the pandemic. The second of these measures visits to restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters. For this reason, we interpret changes in these visits as an indirect measure of away-from-home consumption of goods and services. The Google Mobility Reports data provides changes in household mobility relative to average mobility during the period of January 3 to February 5, 2020. While the data are reported at a daily frequency, we use county-level averages at a monthly frequency.

Our data on house prices are from the Zillow Home Value Index, provided by the real estate company Zillow.[11] We observe county-level house price data at the monthly frequency from January 2019 to August 2021. In order to remove seasonality in the data we compute annual house price growth rates. Finally, we construct real house price growth by deflating the nominal data by annual changes in the CPI.

Figure 3 illustrates the unconditional relationship between household mobility and house price growth in 2020. The red dots represent percentile bins of the household mobility distribution with average house price growth reported for each bin. Panel (a) shows that counties with a larger increase in the amount of time spent at home experienced faster house price growth. Panel (b) shows that counties with a larger decrease in the number of visitors to retail and recreational locations also experienced faster house price growth. Note that there is some non-monotonicity in the tails of the mobility distribution, with counties facing especially large changes in mobility experiencing somewhat lower house price growth. Overall, however, the data is consistent with common movements in time spent at home and housing demand.

We now present a more formal econometric analysis of the relationship between time spent at home and house price growth. Our empirical strategy is to estimate panel data regressions of the following form:

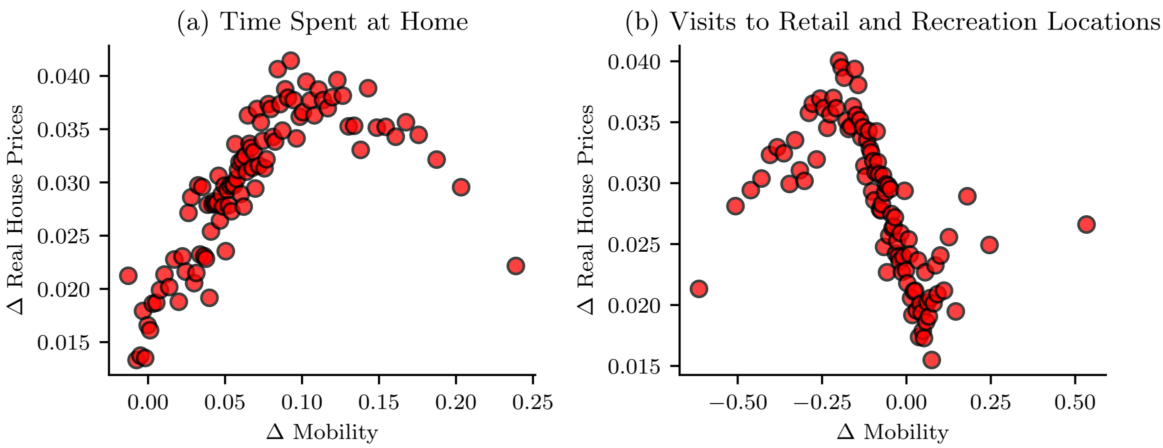
$$\Delta \log P_{c,t} = \beta \Delta \text{Mobility}_{c,t} + \gamma X_{c,t} + \alpha_s + \alpha_{t \leq June2020} + \epsilon_{c,t} \tag{1}$$

where $\Delta \log P_{c,t}$ is the real annual growth rate of house prices in county c at time t, $\Delta\text{Mobility}_{c,t}$ is the change in household mobility relative to the pre-pandemic period, $X_{c,t}$ is a vector of control variables, and α_s are state-level fixed effects, and $\alpha_{t\leq June2020}$ is a dummy variable for observations in the first half of 2020. We are interested in the parameter β, which measures the response of house prices to changes in time spent at home.

[10]See https://www.google.com/covid19/mobility/data_documentation.html?hl=en for an explanation of the various measures of household mobility.

[11]Like the Case-Shiller index, the Zillow Home Value Index accounts for changes in the composition of houses sold at different times by measuring changes in the prices of a fixed set of houses over time. See https://www.zillow.com/research/zhvi-methodology-2019-deep-26226/ for details.

Figure 3: Changes in mobility and house prices



Notes: Binned scatter plots of changes in household mobility against annual real house price growth. Panel (a) sorts on percentiles of changes in average duration at own place of residence. Panel (b) sorts on percentiles of changes in average duration away from home. Changes in household mobility throughout 2020 are calculated relative to the 5-week period of 3 January to 6 February 2020. The latter is from the Google mobility dataset, which uses anonymized and aggregated GPS data from personal cellphones.
Source: Authors' calculations using data from Google, Opportunity Insights, and Zillow.

Data on our control variables come from several sources. We use annual county-level employment growth data from the BLS Local Area Unemployment statistics, county-level population estimates for 2019 from the American Census, local per-capita adjusted gross income from the 2018 IRS Statistics of Income, and the share of total land unavailable for building on as a proxy for county-level housing supply elasticity from Lutz and Sand (2019).[12] Our state-level fixed effects control for potential differences in the way in which state governments responded to the pandemic, for example, via more or less stringent lockdowns. Our dummy variable for the months in the first half of 2020 $\alpha_{t \leq June2020}$ controls for the significant disruptions in real estate markets that occurred in the early months of the pandemic. This captures the non-monotonic relationship between mobility and prices illustrated in Figure 3, which is mostly due to data in the early months of 2020.

While our control variables help to account for likely confounding factors, the cross-sectional variation in house prices may be correlated with other unobserved variables that also affect mobility. For example, counties with more severe lockdowns may have had larger declines in income that suppressed house prices. Since more strict lockdowns would be associated with more time spent at home but also lower house prices through the income channel, we would expect OLS estimates of β from Equation 1 to be biased towards zero.

We address this endogeneity problem by estimating Equation (1) via two-stage-least-squares using a shift-share style instrument for household mobility.[13] To construct our instrument, we interact the local share of employment that can feasibly be carried out at home with a time-

[12] Lutz and Sand (2019) estimate land availability in the same way as Saiz (2010) but provide more geographically disaggregated measures than the MSA-level measures reported by Saiz (2010).
[13] For recent discussions of shift-share instruments see Goldsmith-Pinkham, Sorkin, and Swift (2020).

varying measure of the intensity of the pandemic. The first (share) component of the instrument is taken from Dingel and Neiman (2020) who estimate occupation- and industry-level proxies for the share of jobs that can be conducted at home. These jobs are often referred to as Working From Home (WFH) jobs. To produce county-level WFH shares, we combine industry-level shares from Dingel and Neiman (2020) with county-level shares of total employment in each industry from the 2019 County Business Patterns survey.[14] The second (shift) component of the instrument uses a time-varying state-level measure of pandemic intensity. We use state-level observations on the confirmed number of COVID-19 deaths from data collated by authors at Oxford University (Hale et al., 2021).[15]

Our shift-share instrument is likely to be a good predictor of household mobility. Conditional on the same intensity of pandemic shock within a state, counties with more WFH workers are likely to experience a larger increase in time spent at home and less time spent away from home. The exogeneity of our instrument relies on the shares of WFH employment being independent of other shocks to house prices during the pandemic, conditional on controls.[16] While ability to work from home is pre-determined since most jobs were chosen prior to the onset of the pandemic, Dingel and Neiman (2020) note that remote work is positively correlated with income across occupations, industries, and locations. Additionally, remote workers were less likely to to become unemployed than those whose jobs required them to work *in situ* (Dey et al., 2020). For this reason, we control for both the level of income and changes in employment over the course of the pandemic. Finally, our state-level fixed effects ensure that we are comparing counties within states facing the same level of pandemic intensity. For related reasons, we cluster all standard errors at the state level.

Table 1 reports our OLS and 2SLS estimates of Equation (1). Columns (1) and (2) report our OLS results. Column (1) suggests that a 10 percent increase in time spent at home during 2020 is associated with 1.25 percent faster annual house price growth. Column (2) suggests that a 10 percent decrease in the number of visits to retail and recreation locations is associated with 0.11 percent faster house price growth. Columns (3) and (4) report our 2SLS estimates using the shift-share instrument for household mobility. We find that a 10 percent increase in time spent at home is associated with 4.57 percent faster house price growth. Additionally, a 10 percent larger decline in the number of visits to retail and recreation locations is associated with a 1.28 percent larger increase in house prices.

Table 1 shows that our 2SLS estimates are statistically significantly larger in absolute value than our OLS estimates. These differences are consistent with unobserved pandemic shocks that generate larger declines in household mobility in counties that also faced weaker housing

[14] Dingel and Neiman (2020) classify nearly 1000 US occupations as either able or unable to WFH. They then aggregate this classification in various ways, including at the level of two- and three-digit NAICS codes. While Dingel and Neiman (2020) provide MSA-level data, they do not provide data for more disaggregated levels of geography. We combine WFH and County Business Patterns data at the two-digit NAICS code level to produce a county-level measure.

[15] We also consider alternative instruments constructed using the confirmed number of COVID-19 cases and the stringency of lockdowns. Our results are similar across these different instruments. See discussion below.

[16] This is the exogeneity assumption for shift-share instruments discussed in Goldsmith-Pinkham, Sorkin, and Swift (2020).

demand. For example, areas with more severe COVID-19 outbreaks that forced people to stay home are also likely to have suffered larger declines in local income, which tends to reduce demand for housing.

Table 1: House Price Response to Changes in Local Mobility

	Real 12-month house price growth			
	(1)	(2)	(3)	(4)
Δ Mobility: Time At Home	0.125***		0.457***	
	(0.015)		(0.116)	
Δ Mobility: Visitis to Retail, Recreation		−0.011**		−0.128***
		(0.005)		(0.036)
Δ Employment	0.027	−0.033**	0.220***	0.108***
	(0.017)	(0.013)	(0.064)	(0.040)
ln(Population)	0.008***	0.008***	0.006***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
ln(Income Per Capita)	−0.015***	−0.011***	−0.027***	−0.018***
	(0.004)	(0.004)	(0.005)	(0.005)
Land Unavailability	−0.014**	−0.015**	−0.009	−0.004
	(0.006)	(0.006)	(0.006)	(0.008)
$\mathbb{1}(t \leq \text{June 2020})$	−0.007***	−0.007***	−0.009***	−0.009***
	(0.001)	(0.001)	(0.002)	(0.002)
Observations				
Total	13,890	13,890	13,890	13,890
Counties	1,442	1,442	1,442	1,442
Method	OLS	OLS	2SLS	2SLS
State Fixed Effects	Y	Y	Y	Y
State-Clustered Standard Errors	Y	Y	Y	Y
First Stage F-statistic	–	–	15.16	34.85
Adjusted R-squared	0.27	0.25	0.15	0.05

Notes: Columns (1) and (2) are OLS regressions, and Columns (3) and (4) are 2SLS regressions. The instrument for mobility is the interaction between the county-level share of workers most easily able to work from home with state-level confirmed COVID deaths over time. All specifications include county-level controls for employment growth rates, population, per-capita income, land unavailability, in addition to a dummy for months prior to July 2020, and state fixed effects. All standard errors and first-stage F-statistics clustered at the state level.
Sources: Authors' calculations using data from BLS, Census, Dingel and Neiman (2020), Google Mobility Reports, Hale et al. (2021), Lutz and Sand (2019), Zillow

We also consider several robustness checks of our main empirical results. First, in Table B.7 in Appendix B, we re-estimate our 2SLS regressions using alternative versions of the shift-share instrument for mobility. Columns (1) and (2) restate the main results discussed in Table 1 above. Columns (3) and (4) construct an instrument using the interaction between the share of WFH employment with state-level confirmed COVID-19 cases, rather than confirmed deaths. This instrument is weaker than our baseline instrument, as indicated by first-stage F-statistics below 10. Nevertheless, we find very similar effects of changes in mobility on house prices as in our baseline estimates. Columns (5) and (6) construct an instrument using the interaction between the share of WFH employment with a state-level lockdown stringency index (see Hale et al., 2021). These estimates also suggest that more time spent at home is associated with faster house price growth. However, these estimates are statistically significantly smaller than our baseline estimates. Finally, columns (7) and (8) construct an instrument using the interaction between county-level Republican vote shares in the 2016 presidential election with state-level COVID-19 deaths (MIT Election Data and Science Lab, 2018).[17] These estimates are larger than but not statistically significantly different from our baseline results.

Second, in Table B.8 in Appendix B we investigate whether our results are sensitive to the choice of data sample. Column (2) uses data from both 2020 and 2021. In this specification we also include a dummy variable for the year 2021. The 2SLS estimate is larger than but not statistically significantly different from our baseline estimate. Column (3) only uses data from the second half of 2020, by which time COVID-19 had spread throughout the US. This specification produces very similar results to our baseline estimates. Finally, Column (4) again uses data from 2020 but excludes data from New York and Washington states, since these states were especially hard hit early in the pandemic when the shock was relatively new and potentially more disruptive. Again, we find no statistically significant difference in our estimates.

Third in Table B.9 in Appendix B we consider whether rents respond to stay-at-home shocks in a similar way to house prices.[18] We might expect that the increase in demand for housing applies to both owned and rented houses. We find that the response of rents to stay-at-home shocks is similar to house prices, although the effects are much smaller. We find that a 10 percent increase in time spent at home is associated with a 0.1 to 0.9 percent increase in rents.

3. Quantitative Model

3.1. Household Environment

Demographics. Households live for a finite number of periods with their age indexed by $j \in [1, ..., J]$. Each household splits its life between working and retirement, with the final period of working life at age J_{ret} and retirement commencing the following period. Households face an age-dependent probability of death π_j each period, and can live up to a maximum age of J.

Preferences. Households maximize expected lifetime utility, which takes the form:

$$\mathbb{E}_0 \sum_{j=1}^{J} \beta^{j-1} \left[(1-\pi_j) u(c_{a,j}, c_{h,j}, s_j) + \pi_j \nu(w_j) \right]$$

where $u(\cdot)$ is the flow utility function, $\nu(\cdot)$ is a warm-glow bequest function, β is the discount factor, and π_j is the probability of death at age j. Flow utility is defined over non-durable consumption away from the home c_a, non-durable consumption at home c_h, and consumption of housing services s. Bequests are defined over net wealth remaining at the time of death w.

[17] Engle, Stromme, and Zhou (2020) document that counties with higher Republican vote shares had smaller reductions in household mobility during the pandemic.

[18] Zillow provides data on rents by zip code, which we aggregate up to the county level.

Flow utility is the standard CRRA function over a CES aggregate of away-from-home consumption c_a and a home consumption bundle x_h:

$$u(c_a, c_h, s) = \frac{1}{1-\sigma}\left[\alpha c_a^{1-\vartheta} + (1-\alpha)x_h(c_h, s)^{1-\vartheta}\right]^{\frac{1-\sigma}{1-\vartheta}}$$

where σ is risk aversion, α is the relative taste for consumption away from home, and $1/\vartheta$ is the elasticity of substitution between away-from-home consumption and the home bundle.[19] The home bundle is a Cobb-Douglas combination of at-home consumption c_h and housing services s:

$$x_h = c_h^{\phi} s^{1-\phi}$$

where ϕ is the share of expenditure on the home bundle allocated to at-home consumption. Our setup resembles models of home production (see, for example, Benhabib, Rogerson, and Wright, 1991; McGrattan, Rogerson, and Wright, 1997; Rogerson and Wallenius, 2016), but where housing services are the relevant household input rather than time.

Our main pandemic experiment in Section 5 is a stay-at-home shock given by a decline in the parameter α. Consistent with the data presented in Section 2.2, the stay-at-home shock shifts consumption from away-from-home goods towards the home bundle. In Appendix C.1 we present a simple static equilibrium model with the same preferences over consumption and show analytically that a stay-at-home shock results in greater housing demand and higher house prices.

Finally, households enjoy a warm-glow bequest motive over net wealth left behind if dying at age j:

$$\nu(w_j) = B\frac{w_j^{1-\sigma}}{1-\sigma}$$

where $B > 0$ captures the strength of the bequest motive, and net wealth w_j is defined as the sum of liquid assets and housing wealth.

Endowments. Households receive stochastic labor income while working and a constant pension when retired. When working, labor income is the combination of a deterministic life-cycle component χ_j and a stochastic component z_j. The stochastic component z_j follows a log-AR(1) process with persistence ρ_z and standard deviation of innovations ϵ_z. In addition, households may become unemployed during their working life. Unemployed households receive a fraction ω_u of their employed earnings potential. Employment status follows an age-dependent Markov chain with transition matrix Γ_j. Transitions into and out of employment at age j are given by

$$\Gamma_j = \begin{bmatrix} 1-d_j & d_j \\ f & 1-f \end{bmatrix}.$$

[19]In a multi-sector New Keynesian model, Guerrieri et al. (2021) show that sectoral supply shocks can have spillover effects on demand when the inter-temporal elasticity of substitution is larger than the the intra-temporal elasticity of substitution across goods. We do not model general equilibrium in goods markets in this paper, so the spillover channel is not active here.

where unemployed households find a job with a constant probability f, but the job separation rate for employed households d_j depends on their age.[20] Our calibration in Section 4 generates declining job separation rates by age, which is consistent with the observed decline in unemployment rates over the life-cycle. Finally, in retirement households receive a constant pension equal to a fraction ω_{ret} of their earnings in the last year of working life.

Let y_j denote earnings at age j, and let $e \in \{0, 1\}$ denote working status reflecting unemployment and employment, respectively. Then household earnings is given by

$$y_j = \begin{cases} \chi_j \cdot z_j & \text{if } j \leq J_{ret}, \quad e = 1 \quad \text{(working-age, employed)} \\ \omega_u \cdot \chi_j \cdot z_j & \text{if } j \leq J_{ret}, \quad e = 0 \quad \text{(working-age, unemployed)} \\ \omega_{ret} \cdot \chi_{J_{ret}} \cdot z_{J_{ret}} & \text{if } j > J_{ret} \quad \text{(retired)} \end{cases}$$

In our experiments described in Section 5, households may also receive government transfers, which stand in for stimulus checks and expanded unemployment benefits paid to households during the pandemic.

Housing. Housing services can be acquired by renting at the per-unit rental rate P_r or by owning property purchased at the per-unit house price P_h. Renters can costlessly adjust the size of their dwelling each period. In contrast, homeowners face a transaction cost F_h, proportional to the value of their house, whenever they wish to sell their property. homeowners must also pay housing maintenance costs δ each period, which are proportional to the value of their house. Rental units and owner-occupied houses are chosen from discrete sets $\mathcal{H}_r$ and $\mathcal{H}_o$, respectively.

Liquid assets. Households can save or borrow in a risk-free liquid asset a. When saving, the return on assets is r. Homeowners can finance property purchases by borrowing against the value of their property, which implies a negative liquid asset balance. This simple borrowing structure stands in for the more complex mortgages modelled in the literature.[21] Unsecured borrowing (i.e. by renters) is not allowed. Mortgage balances accrue interest at the rate r_m, where $r_m > r$ reflects a spread over the risk-free rate capturing unmodeled mortgage risk- and term-premia. Thus, the interest rate is a function of the household's asset position and is given by:

$$r(a) = \begin{cases} r & \text{if } a \geq 0 \\ r_m & \text{if } a < 0 \end{cases}$$

Borrowers pay an origination cost F_m proportional to the size of the mortgage when they take out a new purchase mortgage or when they refinance. We assume that refinancing occurs

[20] Graham and Ozbilgin (2021) study the effects of pandemic lockdowns in a heterogeneous agent model with labor search and age- and industry-dependent employment status. Job separation rates endogenously respond to both pandemic shocks and government wage subsidies. In the current paper, we assume that job separation rates evolve exogenously. See Section 4.1 for details.

[21] We assume one-period mortgage debt for tractability, but recent papers have studied models with long-term mortgage contracts. See, for example, Garriga, Kydland, and Šustek (2017), Kaplan, Mitman, and Violante (2020a), Boar, Gorea, and Midrigan (2020), and Karlman, Kinnerud, and Kragh-Sorensen (2021).

any time the borrower chooses to increase the mortgage balance without purchasing a new house. At origination, new mortgages a' are subject to a maximum loan-to-value (LTV) ratio constraint:

$$a' \geq -\theta_m P_h h'$$

where θ_m is the maximum LTV ratio, and $P_h h'$ is the value of the current house (either a new purchase, or an existing property). New mortgages are also subject to a payment-to-income (PTI) constraint, following Greenwald (2018):

$$r_m a' \geq -\theta_y y_j$$

where $r_m a'$ is the minimum required mortgage payment, and θ_y is the maximum PTI ratio.

Households begin life with no owned housing or mortgage debt. However, households may receive bequests in the form of a positive initial liquid asset balance. See Section 4 for details.

3.2. Household Decision Problems

Households enter a period at age j with the state vector $\mathbf{s} = (a, h, z, e)$, where a is liquid assets or debt, h is current owner-occupied housing (set to zero for renters), z is the persistent component of labor income, and e is employment status. A household chooses between renting, maintaining its current housing position, and adjusting its house size and/or mortgage debt. A household of age j with state $\mathbf{s}$ solves:

$$V_j(\mathbf{s}) = \max\left\{V_j^R(\mathbf{s}), V_j^N(\mathbf{s}), V_j^A(\mathbf{s})\right\}$$

where V_j^R is the value function of a renter, V_j^N is the value function of an owner that does not adjust its house size or increase its mortgage debt, and V_j^A is the value function of an owner that adjusts its house size and/or mortgage.

A household who chooses to rent solves:

$$\begin{aligned} V_j^R(\mathbf{s}) = & \max_{c_a, c_h, s, a'} u(c_a, c_h, s) + \beta \mathbb{E}\left[(1-\pi_{j+1})V_{j+1}(\mathbf{s}') + \pi_{j+1}\nu(w')\right] \\ & \text{s.t. } c_a + c_h + P_r s + a' = y_j + (1 + r(a))a + (1 - F_h)P_h h \\ & \quad s \in \mathcal{H}_r, \; a' \geq 0, \; h' = 0 \end{aligned}$$

The problem for a non-adjusting household is:

$$\begin{aligned} V_j^N(\mathbf{s}) = & \max_{c_a, c_h, a'} u(c_a, c_h, h) + \beta \mathbb{E}\left[(1-\pi_{j+1})V_{j+1}(\mathbf{s}') + \pi_{j+1}\nu(w')\right] \\ & \text{s.t. } c_a + c_h + \delta P_h h + a' = y_j + (1 + r(a))a \\ & \quad h' = h, \; a' \geq \min\{0, a\} \end{aligned}$$

where the constraint on the liquid asset choice indicates that homeowners with a mortgage cannot increase the size of their debt.

The problem for an adjusting household is:

$$
\begin{aligned}
V_j^A(\mathbf{s}) = \quad & \max_{c_a, c_h, h', a'} u(c_a, c_h, h')\beta\mathbb{E}\left[(1-\pi_{j+1})V_{j+1}(\mathbf{s}') + \pi_{j+1}\nu(w')\right] \\
\text{s.t. } & c_a + c_h + \delta P_h h' + a' + \psi(a, a', h, h') = y_j + (1 + r(a))a + \mathbb{1}_{h' \neq h}\big((1 - F_h)P_h h - P_h h'\big) \\
& h' \in \mathcal{H}_o \\
& a' \geq -\theta_m P_h h' \\
& r_m a' \geq -\theta_y y_j
\end{aligned}
$$

The function $\psi(a, a', h, h')$ represents the mortgage origination cost, which is incurred if the homeowner borrows when purchasing a new house, or if it remains in its current house but chooses to increase the size of its mortgage (i.e. refinances its mortgage):

$$
\psi(a, a', h, h') = \begin{cases} F_m|a'| & \text{if} \quad h' \neq h \;\; \& \;\; a' < 0 \\ F_m|a'| & \text{if} \quad h' = h \;\; \& \;\; a' < a < 0 \\ 0 & \text{otherwise.} \end{cases}
$$

3.3. Equilibrium

We assume that a competitive rental firm trades housing units and rents them out to households at the market rental rate P_r. Accordingly, the supply of rental housing is perfectly elastic at the market rental rate, which is given by the user cost relationship:

$$
P_r = (1 + \delta + \kappa)P_h - \frac{1}{1+r}\mathbb{E}[P_h'] \tag{2}
$$

where κ is an operating cost, proportional to the value of the rental firm's housing stock. The operating cost κ creates a wedge between the user cost of owning a house in the model and the cost of renting it, which provides households with an incentive to own.

The stationary equilibrium of the model consists of the household value functions and decision rules, prices P_h and P_r, and a stationary distribution of households such that: value functions and decision rules are consistent with household optimization, the rental market clears, the housing market clears, and the distribution of households is consistent with decision rules and the exogenous processes for labor income and employment. We provide a formal definition of the equilibrium in Appendix C.3.[22]

4. Calibration

4.1. External Parameters

Below we describe our choices for parameter values that are assigned directly or taken from other studies. These externally calibrated parameters are listed in Table 2.

[22] Note that since our primary focus is on the effect of the pandemic on housing markets, we do not solve for equilibrium in goods markets or with respect to government decisions. We leave a more complete analysis for further research.

Demographics and preferences. The model period is one year. Households enter the economy aged 25, retire after age 65 ($J_{ret} = 41$), and death occurs with certainty at age 80 ($J = 56$). The age-dependent death probabilities π_j are taken from male death probabilities reported in Social Security Administration Actuarial Tables.

We set $\sigma = 2$ which is standard in the literature. We set the elasticity of substitution between away-from-home consumption and the home bundle to $1/\vartheta = 2$. There are no direct estimates of this particular elasticity. However, we think our choice is reasonable since Aguiar and Hurst (2007) and Nevo and Wong (2019) estimate elasticities of substitution between time and goods used in home production of around 2, and McGrattan, Rogerson, and Wright (1997) estimate elasticities of substitution between home and market produced goods of around 1.7.

Endowments. We take the parameters that govern the idiosyncratic income process from Kaplan, Mitman, and Violante, 2020a, who set the persistence of the log-AR(1) shocks $\rho_y = 0.97$ and the standard deviation of innovations $\sigma_y = 0.2$. The deterministic life-cycle profile of income χ_j follows a tent-shape, taken from Ma and Zubairy (2021):

$$\chi_j = 1 + \xi \left(1 - \frac{\mid j - J_{peak} \mid}{J_{peak} - 1}\right) \ \forall\ j \leq J_{ret}$$

where J_{peak} is the peak age for earnings, and ξ captures the rise in earnings over the life-cycle. We set the peak earnings age to be 50 ($J_{peak} = 26$), and $\xi = 0.5$ so that, on average, labour income rises by 50 percent between entering the labor force and the peak earnings age. These parameters generate a reasonable approximation to the life-cycle profile of median household labor income in the 2019 SCF (see Figure 4(b)). The unemployment insurance replacement rate is set to $\omega_u = 0.5$ following Krueger, Mitman, and Perri (2016). Finally, we normalize median labor income of employed working-age households in the model to one.

In the first period of life households receive a bequest with probability π_b. Conditional on bequest, households receive a fraction ω_b of their initial period income. We calibrate these parameters using data on households aged 20 to 25 in the 2019 Survey of Consumer Finances. We set $\pi_b = .69$ based on the fraction of young households with positive net worth, and we set $\omega_b = 0.57$ based on the median net worth-to-income ratio for young households with positive net worth.

Interest rates, mortgages, transaction costs and depreciation. We set the risk-free interest rate to $r = 0.02$ and the mortgage interest rate $r_m = 0.04$. We set the LTV limit on mortgages $\theta_m = 0.9$ and the maximum PTI ratio $\theta_y = 0.5$ based on evidence from Greenwald, 2018. The mortgage origination cost F_m is set to 0.5 percent of the mortgage balance at origination based on average origination fees and discount points for 30-year mortgages using the Freddie Mac Primary Mortgage Market Survey, accessed via FRED. The transaction cost for selling a house F_h is set to 6 percent of the house value, which is standard. The depreciation rate of owner-occupied housing is set to 3 percent based on evidence from Harding, Rosenthal, and Sirmans (2007).

Table 2: Externally Calibrated Model Parameters

Description	Parameter	Value	Source
Maximum age	J	56	Standard
Retirement age	J_{ret}	41	Standard
Life-cycle income, peak age	J_{peak}	26	Ma and Zubairy (2021)
Life-cycle income, growth	ξ	0.50	Ma and Zubairy (2021)
Productivity standard deviation	σ_z	0.20	Kaplan, Mitman, and Violante, 2020a
Productivity persistence	ρ_z	0.97	Kaplan, Mitman, and Violante, 2020a
Retirement replacement rate	ω_{ret}	0.50	Díaz and Luengo-Prado (2008)
Unemployment replacement rate	ω_u	0.50	Krueger, Mitman, and Perri (2016)
Fraction receiving bequest	π_b	0.69	SCF
Bequest-to-income ratio	ω_b	0.57	SCF
Housing depreciation rate	δ	0.03	Harding, Rosenthal, and Sirmans (2007)
Maximum LTV ratio	θ_m	0.90	Greenwald (2018)
Maximum PTI ratio	θ_y	0.50	Greenwald (2018)
House sale cost	F_h	0.06	Standard
Mortgage origination cost	F_m	0.005	FRED
Risk aversion	σ	2	Standard
Elasticity of substitution	$1/\vartheta$	2	Aguiar and Hurst (2007)
Interest rate	r	0.02	FRED
Mortgage interest rate	r_m	0.04	FRED

4.2. Fitted Parameters

Unemployment process. The parameters of the age-dependent Markov chain for employment Γ_j are calibrated to match the life-cycle profile of unemployment in the US.[23] We assume that the age-dependent job separation rates evolve according to an AR(1) process:

$$d_j = (1 - \rho_d)\mu_d + \rho_d d_{j-1}. \tag{3}$$

The job finding rate f is constant across ages. We then use simulated method of moments to calibrate five parameters: the job finding rate f, the long-run average separation rate μ_d, the persistence of separation rates across age ρ_d, the initial separation rate d_1, and the initial fraction of unemployed households $\pi_{u,1}$. Using data from the Current Population Survey from 2017 to 2019, we match average unemployment rates across workers in five-year age bins from 25 to 65.[24] Table 3 Panel A and Figure 4(a) shows that this simple process for employment transitions matches the pre-pandemic life-cycle profile of unemployment extremely well.

Preferences and housing. We calibrate the remaining parameters listed in Table 3 to minimize the sum of squared deviations of seven model moments from their empirical counterparts.

[23]Our calibration strategy follows Graham and Ozbilgin (2021), who calibrate an AR(1) process to generate separation rates for every age in the model while matching aggregated unemployment rates in 5-year age bins.

[24]By 2017, unemployment rates across age groups had converged to their pre-financial crisis levels.

Table 3: Internally Calibrated Model Parameters and Target Moments

Parameter		Value	Moment	Model	Data	Source
A. Employment Process Parameters						
Job finding rate	f	0.976	Unemployment: 25–29	0.043	0.045	CPS
Separation rate, persistence	ρ_d	0.854	Unemployment: 30–34	0.035	0.037	CPS
Separation rate, mean	μ_d	0.028	Unemployment: 35–39	0.031	0.031	CPS
Separation rate, age 25	$d_{j=1}$	0.049	Unemployment: 40–44	0.030	0.030	CPS
Unemployment rate, age 25	$\pi_{u,j=1}$	0.050	Unemployment: 45–49	0.029	0.028	CPS
B. Preference and Housing Market Parameters						
Discount factor	β	0.840	Networth-Income, median	2.054	2.007	SCF
Bequest preference	B	43.977	NW Over 65/NW Under 65	1.646	1.735	SCF
Away-from-home consumption	α	0.563	Away-from-home expenditure share	0.383	0.386	CEX
At-home consumption	ϕ	0.307	At-home expenditure share	0.210	0.211	CEX
Minimum house size	$\underline{h}$	2.995	Homeownership	0.681	0.666	SCF
Housing grid spacing	Δ_h	0.604	House Value-to-Income, p75-to-p50	1.714	1.697	SCF
Corporate rental cost	κ	0.021	Homeownership, age$\leq$35	0.430	0.440	SCF

Notes: SCF data taken from the 2019 survey. Median consumption shares computed using sample averages in CEX data from 2017 to 2019. Unemployment rates computed using averages of monthly rates in CPS data from 2017-2019.
Sources: Authors' calculations using CEX, CPS, SCF.

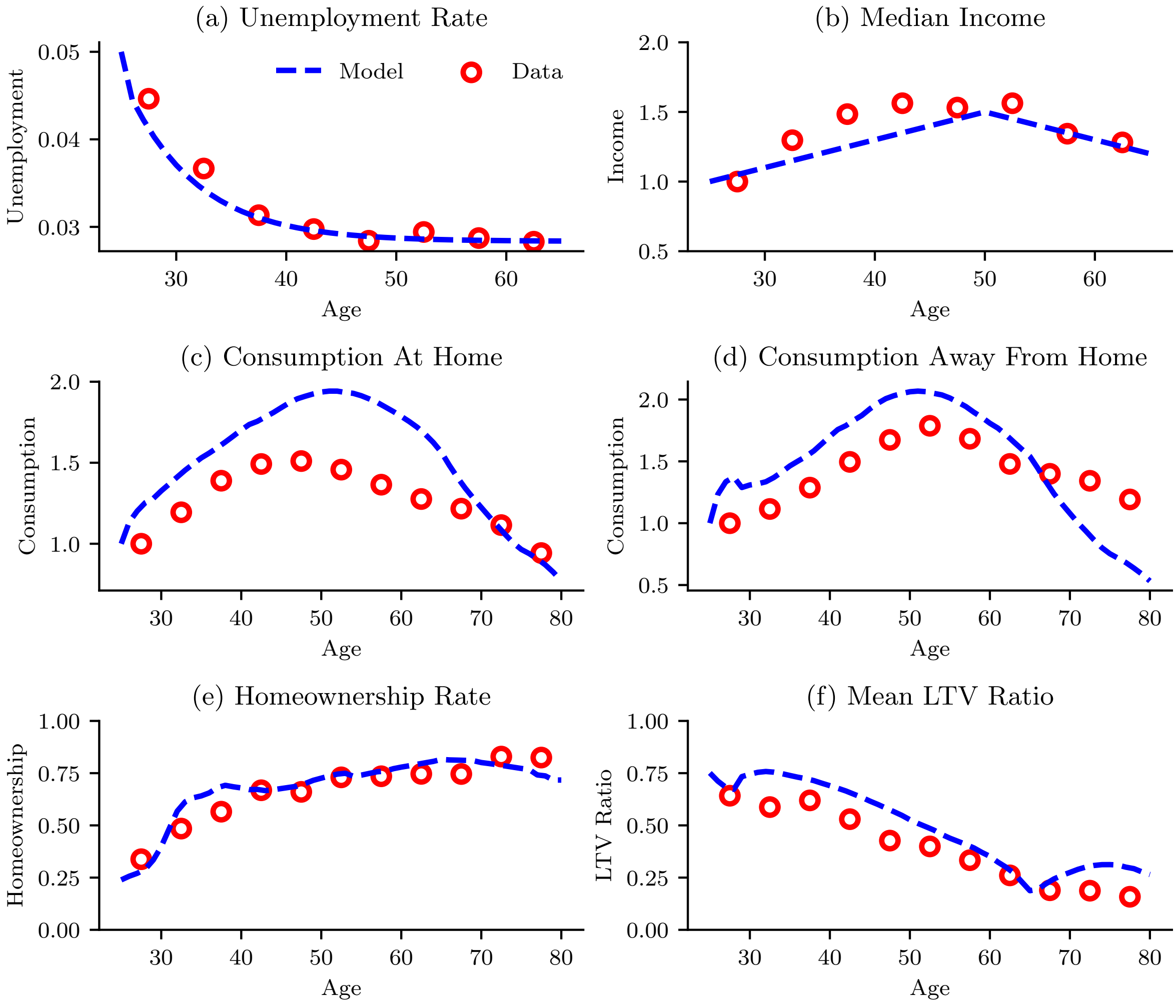
Table 3 Panel B shows that the model matches the targeted moments reasonably well. These computed parameters are jointly identified by the targeted moments, but we outline which moments have the largest influence on each parameter below.

The annual discount factor is $\beta = 0.84$, which matches a median household net worth to income ratio of 2.0. The strength of the bequest motive is $B = 44.0$, which targets a ratio of 1.7 for the net worth of households older than 65 to those under 65. The relative taste for away-from-home consumption $\alpha = 0.56$ matches a median household expenditure share of around 37 percent (as shown in Figure 2(b)). Similarly, the share of at-home consumption in the home consumption bundle is set to $\phi = 0.31$, which helps match a median expenditure share of at-home consumption of 21 percent (also see Figure 2(b)). The rental firm's operating cost is $\kappa = 0.02$, which helps to match a homeownership rate of 44 percent for households under the age of 35.

We assume that rental and owner-occupied house sizes are chosen from overlapping discrete sets with three sizes in each: $\mathcal{H}_r = \{h_1, h_2, h_3\}$ and $\mathcal{H}_o = \{h_3, h_4, h_5\}$. Two parameters control the distribution of house sizes: the minimum owner-occupied house size h_3 and the log-distance between consecutive sizes Δ_h.[25] We set the minimum owner-occupied house size to $h_3 = 3$ to target a homeownership rate of 67 percent. The log-distance parameter is $\Delta_h = 0.6$, which helps to match the difference between the house value-to-income ratios at 75th and 50th percentiles of the housing-to-income distribution.

[25]The five house sizes are set as $h_i = \exp(\log(h_3) + (i - 3) \times \Delta_h)$ for $i = 1, ..., 5$.

Figure 4: Model Fit to Life-Cycle Statistics



Notes: All statistics in the data computed for five-year age bins starting from age 25. Panels (b), (c), and (d) normalize both model and data to one at the first age. Panel (f) reports the average LTV ratio for all homeowners. *Sources:* Authors' calculations using data from the CEX, CPS, and SCF.

4.3. Model Fit

Figure 4 shows life-cycle profiles of unemployment, income, consumption, homeownership and mortgage leverage in the model and data. Since we calibrate the unemployment process in the model to match life-cycle unemployment data, it is unsurprising that the model provides a good fit to the data in Panel (a). Our parsimonious "tent-shaped" age-profile for labor income is broadly consistent with the profile of median household income in the SCF, as shown in Panel (b). Panels (c) and (d) show that the model also mimics the hump-shaped life-cycle profiles of both away-from-home and at-home consumption, even though our calibration only targets median expenditure shares across households of all ages. Panel (e) shows that the model provides a reasonable fit to the life-cycle profile of homeownership. Finally, Panel (f) shows that the model reproduces the life-cycle decline in average homeowner leverage very well, even though our calibration does not explicitly target any moments related to household debt.

Table 4: Parameters and Moments Calibrated for the Pandemic Experiment

Parameter	Value	Moment	Model	Data
α_{2020}	0.515	Change in Median At-Home Share of Non-Housing Exp., 2019-2020	0.057	0.057
α_{2021}	0.501	Change in Median At-Home Share of Non-Housing Exp., 2019-2021	0.074	0.073
$r_{m,2020}$	0.032	Change in 30-Year Mortgage Rate, 2019-2020	-0.008	-0.008
$r_{m,2021}$	0.026	Change in 30-Year Mortgage Rate, 2019-2021	-0.014	-0.014
$\varepsilon_{s,2019}$	0.085	Change in Unemployment Rate, 2019-2020	0.059	0.059
$\varepsilon_{f,2020}$	-0.280	Change in Unemployment Rate, 2019-2021	0.022	0.022
$T_{u,2020}$	0.218	Additional UI Per Person/Median Labor Income, 2020	0.218	0.218
$T_{u,2021}$	0.196	Additional UI Per Person/Median Labor Income, 2021	0.196	0.196
$T_{all,2020}$	0.035	Stimulus Checks Per Household/Median Labor Income, 2020	0.035	0.035
$T_{all,2021}$	0.058	Stimulus Checks Per Household/Median Labor Income, 2021	0.058	0.058
ρ_{α,r_m}	0.510	Excess Real House Price Growth, 2019-2020	0.072	0.074

Notes: Data statistics for 2020 are computed as means of monthly data from April 2020. Data statistics for 2021 are computed as means of monthly data up until August 2021. Real house price growth rates are computed using annual growth rates in December 2019 and 2020.
Sources: Authors' calculations using CEX, FRED.

5. Pandemic Experiments in the Quantitative Model

We now study a series of experiments designed to understand the effect of the pandemic on the US housing market. We model the pandemic as four shocks that hit the economy in 2020 and 2021: (1) a stay-at-home shock characterized by a shift in preferences towards consumption at home, (2) a fall in real mortgage rates, (3) an increase in unemployment, and (4) government transfers in the form of stimulus checks and expanded unemployment benefits. We assume the economy is in steady state in 2019 and that all shocks are unexpected prior to the onset of the pandemic. However, the entire sequence of shocks becomes known to households in 2020.

5.1. Calibration of the Pandemic Shocks

The size of each shock is chosen to match empirical observations from 2020 and 2021. Statistics from 2020 are computed as monthly averages starting from April to capture the onset of the pandemic. Table 4 reports the shock parameters and statistics used for calibration. First, there is a decline in the relative taste for away-from-home consumption α. We set the values of α to match the rise in the at-home consumption share of non-housing consumption in 2020 and 2021.[26] Second, the real mortgage interest rate r_m falls in line with the observed decline in real rates in 2020 and 2021.

Third, we implement a parsimonious set of unemployment shocks relative to the recent literature.[27] The unemployment shocks include a rise in the job separation rate for all age groups

[26]Scaling by non-housing consumption, rather than total consumption, means that the targeted consumption shares are not directly affected by endogenous changes in house prices and rents along the transition path.

[27]Fang, Nie, and Xie (2020) and Graham and Ozbilgin (2021) model search and matching models of the labor

and a fall in the job finding rate f. We calibrate these shocks to match the rise in aggregate unemployment in 2020 and 2021 relative to 2019. Although steady state job separation rates vary by age, we assume that separations increase by the same amount ε_d for each age group. This means that the unemployment rate rises by a similar amount for all age groups. The separations shock ε_d occurs at the end of the 2019 period in order to affect unemployment rates in 2020. We then assume that the job separation rate f increases in 2020 so that higher unemployment rates carry over into 2021.

Fourth, we introduce flat-rate payments for unemployed workers and lump-sum transfers in 2020 and 2021 to model the expanded unemployment insurance benefits and stimulus checks paid out under the CARES Act, COVID-related Tax Relief Act of 2020, and the American Rescue Plan Act.[28] Specifically, we assume that all households in the model receive stimulus payments of $2,400 in 2020 and $4,000 in 2021.[29] We assume unemployed households receive extra benefits of $12,000 in 2020 and $10,800 in 2021.[30]

We further assume that after the initial pandemic shocks in 2020 and 2021, the preference parameter α and the mortgage interest rate r_m slowly return to their steady state values following AR(1) processes with common persistence ρ_{α,r_m}. We set ρ_{α,r_m} so that the house price growth rate in 2020 in the model is equal to the excess annual growth rate of real house prices in December 2020 relative to December 2019. The persistence parameter affects the size of the house price boom in the model since the increase in housing demand is front-loaded with respect to the entire sequence of shocks. The longer that households expect to remain at home and the longer that real interest rates remain low, the more households are willing to pay for houses in 2020.[31]

market during the pandemic and study exogenous and endogenous job separation rates, respectively. Carroll et al. (2020) model pandemic shocks by matching both the cross-sectional distribution of unemployment as well as heterogeneity in unemployment duration.

[28]Carroll et al. (2020) presents a detailed study of the consumption response to the CARES Act. They use a heterogeneous agents life-cycle model that matches estimated consumption responses to tax and benefit changes. Unlike the current paper, they do not model the housing market.

[29]We assume households in the model are made up of two people, so we give them two checks for each round of stimulus. The payment of $4,000 in 2021 reflects the $600 checks paid out in late December 2020 and the $1,400 checks paid out in March 2021. The three rounds of stimulus checks also included payments for children, which we do not model. We also ignore the income thresholds at which payments started being reduced. For details of the stimulus payments, see: https://home.treasury.gov/policy-issues/coronavirus/assistance-for-american-families-and-workers/economic-impact-payments.

[30]Federal Pandemic Unemployment Compensation, created under the CARES Act, provided an additional $600/week to all UI recipients from late March to end-July 2020 (17 weeks), for a total of $10,200. The Lost Wages Assistance program provided an additional $300/week from August to September 2020 (6 weeks) for a total of $1,200. The American Rescue Plan Act gave UI recipients an additional $300/week from late December 2020 to September 6 2021 (36 weeks) for a total of $10,800, which we allocate to households in 2021. For details on the additional UI payments see Boesch, Lim, and Nunn (2021) and Ganong et al., 2021.

[31]Figure C.1 in Appendix C.5 illustrates the evolution of aggregate variables in the economy under different assumptions about the persistence of these shocks.

5.2. Aggregate Responses to the Pandemic Shocks

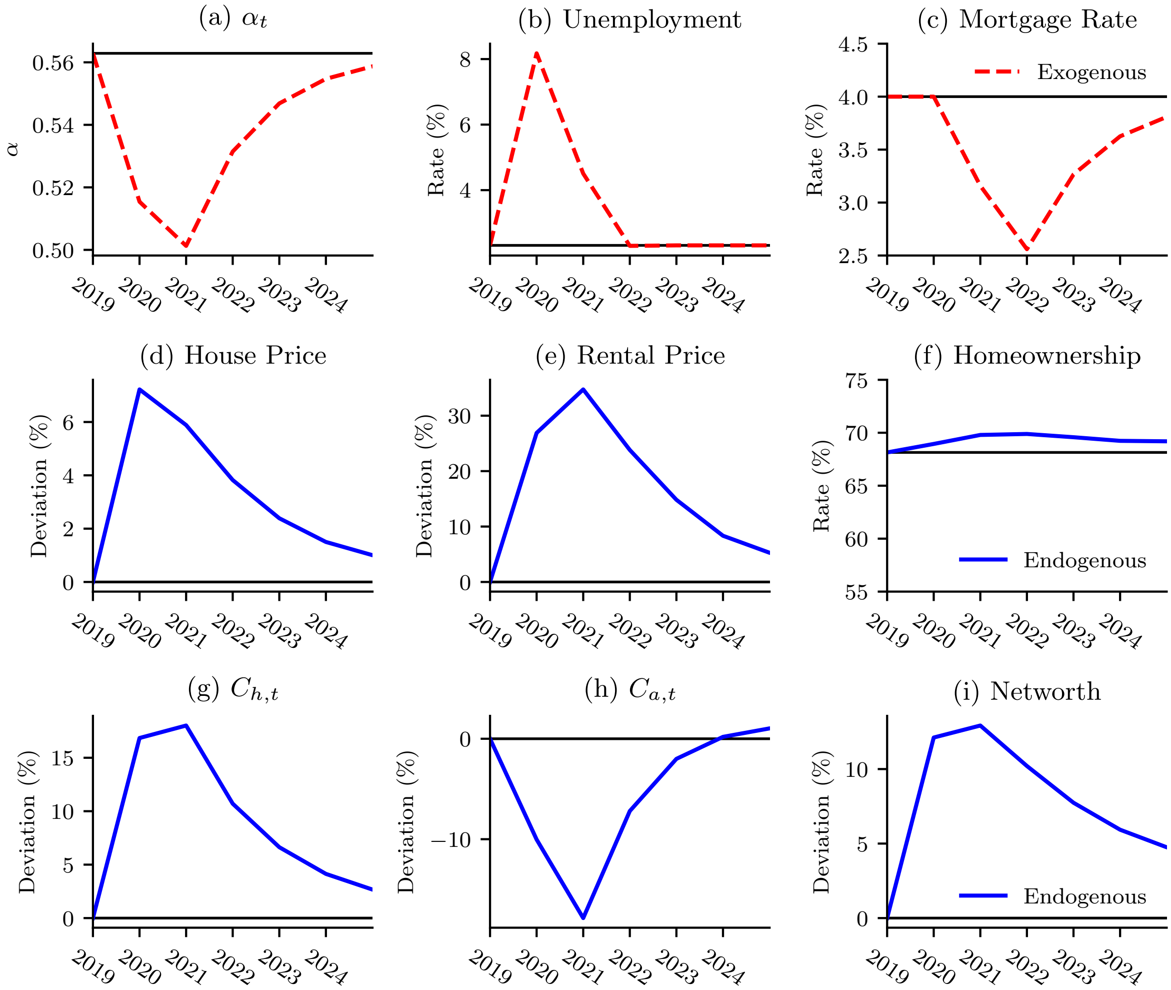
Figure 5 shows the responses of key macroeconomic aggregates in the model to the four pandemic shocks. Panels (a)–(c) show the exogenous paths of the preference parameter α, the unemployment rate, and the mortgage interest rate. Panels (d) and (e) show the endogenous response of the prices of owned and rental housing. Movements in house prices ensure that the overall housing market clears, while changes in rental rates are determined by the user-cost condition in Equation (2). House prices in the model rise by a little over 7 percent, consistent with observed excess house price growth in 2020. Since housing supply is assumed fixed along the transition path, the increase in house prices is due to the increase in housing demand generated by the pandemic shocks. This is reflected in a small increase in the homeownership rate from 68 percent in 2019 to 69.9 percent by 2022 (see panel (f)). Note, however, that rental prices in the model rise by significantly more than is observed in the data.[32] This is entirely due to the user-cost equation, since higher rents compensate the rental firm for the present discounted value of capital losses along the transition path. In Appendix C.5 we solve the model using the same sequence of shocks, but where we assume that housing and rental markets are segmented, and that the supply of both owner-occupied and rental housing are fixed along the transition path. In this version of the model, we solve for a path of house prices and a path of rental prices, such that in each period of the transition the demand for owner-occupied housing equals the owner-occupied supply, and demand for rental housing equals the rental supply. Growth in rents is significantly lower in this version of the model and there no rise in homeownership, but the dynamic responses of other variables are very similar to our baseline results.

Figure 6 decomposes the effect of each of the pandemic shocks on house prices and away-from-home consumption. We re-solve for the general equilibrium transition path of the economy in response to each shock separately, keeping all other exogenous variables fixed at their steady state values. We compare the effect of each shock to the model responses when the economy is hit by all four shocks, with the latter depicted in solid blue lines. The stay-at-home shock (dashed red lines) and the mortgage rate r_m shock (dotted green lines) have the largest effects on housing demand over the course of the pandemic. The stay-at-home shock alone explains 48 percent of the the increase in house prices, while the fall in mortgage rates accounts for 36 percent of the increase in house prices. Fiscal stimulus has a smaller effect on house prices, accounting for 19 percent of the price increase in 2020 (yellow lines with triangle markers). The unemployment shocks (purple lines with circle markers) also have a small effect on house prices; they cause prices to fall by 0.5 percent in 2020. It is worth noting that our model predicts that the large fiscal stimulus more than offsets the decline in housing demand caused by the spike in unemployment. The unemployment shocks have a small effect on housing demand for two reasons. First, the high steady state job finding rate implies that employment quickly recovers after the pandemic. Second, even in steady state, working households are insured by a relatively high replacement rate provided by unemployment insurance.[33]

[32]According to data from FRED, the annual growth rate of the CPI for rent of the primary residence fell from 3.7 percent in 2019 to a low of 1.8 percent in 2021 (FRED code: CUSR0000SEHA).

[33]As Graves (2020) shows, the presence of unemployment insurance significantly dampens the aggregate demand

Figure 5: Impulse Responses for Pandemic Experiment Shocks



Our model suggests that there is little amplification of house prices due to the stay-at-home shocks and falling mortgage rates. Figure 6(a) shows that when the economy is hit by the shift in household preferences and the mortgage rate shock simultaneously (black dashed line with square markers), the house price response is around 84 percent of the price increase in 2020. The sum of the price responses under each of the shocks separately is also around 84 percent of the total price increase.[34] The lack of substantial amplification may seem surprising since falling mortgage rates loosen PTI constraints on mortgage borrowing, and so could potentially relax borrowing constraints at the same time as increased demand for housing due to the stay-at-home shock. To see whether this interaction effect is an important force in the model we compute the share of marginal house buyers for whom the PTI constraint dominates the LTV constraint, following Ma and Zubairy (2021). We define a marginal house buyer as a household

effects of business cycle shocks in heterogeneous agent models.

[34]The lack of substantial amplification is consistent with the model in Kaplan, Mitman, and Violante, 2020a, where a relaxation of borrowing constraints does not amplify the house price response to an increase in expected future housing demand.

Figure 6: Impulse Responses to Separate Pandemic Shocks

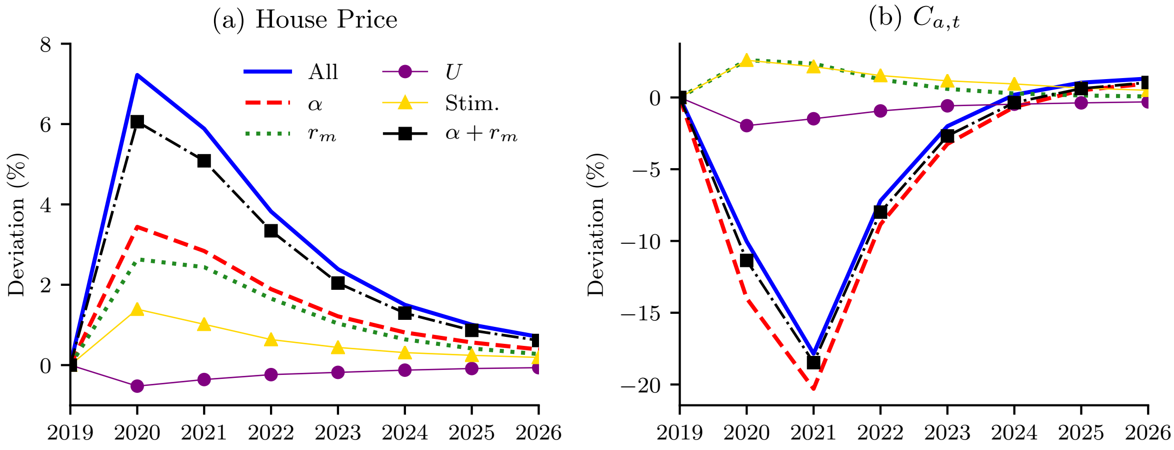


Table 5: Fraction of PTI Dominant Marginal House Buyers

		Pandemic Shocks			
	Steady State	Preferences	Mortgage Rate	Preferences and Mortgage Rate	All Shocks
Fraction PTI-Dominant (%)	7.02	9.15	3.02	3.05	0.93

whose value of purchasing a house is very close to the value of renting:

$$\frac{|V_j^O(a,h,y,e) - V_j^R(a,h,y,e)|}{|V_j^R(a,h,y,e)|} \leq 0.01$$

A marginal buyer is then PTI-dominant if the amount that can be borrowed at the maximum PTI constraint is less than the amount that can be borrowed at the maximum LTV constraint:

$$\frac{\theta_y y_j}{r_m} \leq \theta_m P_h \bar{h}$$

where $\bar{h}$ is the average house size chosen by households in steady state.

Table 5 reports the fraction of PTI-dominant marginal buyers in the steady state and in 2020 under selected pandemic shocks. Since the preference shock increases the demand for housing, more lower-income households want to purchase a house but these households are more likely to face a binding PTI constraint. However, the reduction in mortgage interest rates lowers the PTI ratio on new loans and so fewer marginal buyers are likely to run up against the PTI constraint. The combination of preference and mortgage shocks also results in fewer potentially PTI-constrained house buyers compared to steady state. When the economy is hit by all four pandemic shocks, the proportion of potentially PTI-constrained marginal buyers falls to just 0.9%, as the stimulus shocks also increase household income. Overall, however, the fraction of marginal buyers likely to be affected by changes in PTI is small at less than 10 percent in all experiments. Accordingly, the model generates very little amplification due to the interaction

Table 6: Proportion of Households by Housing Tenure, Partial Equilibrium

	Renters	Homeowners				
		First Time	Upsizing	Downsizing	Refinancing	Not Adjusting
Steady state	31.9	1.9	1.0	0.6	14.8	49.9
Preference shocks	30.1	3.3	1.6	0.4	15.0	50.9
Mortgage rate shocks	29.4	3.9	1.5	0.3	15.2	47.8
Unemployment shocks	32.3	1.8	0.9	0.8	17.3	45.7
Stimulus shocks	30.8	2.5	1.3	0.4	14.9	51.2
All Shocks	27.2	5.9	1.8	0.1	18.0	51.0

Notes: Fraction of households by type of housing decision, reported as a percent of all households. The first row computes fractions in steady state. All other rows compute fractions in the first period of the transition path following pandemic shocks under partial equilibrium (i.e. no price adjustment).

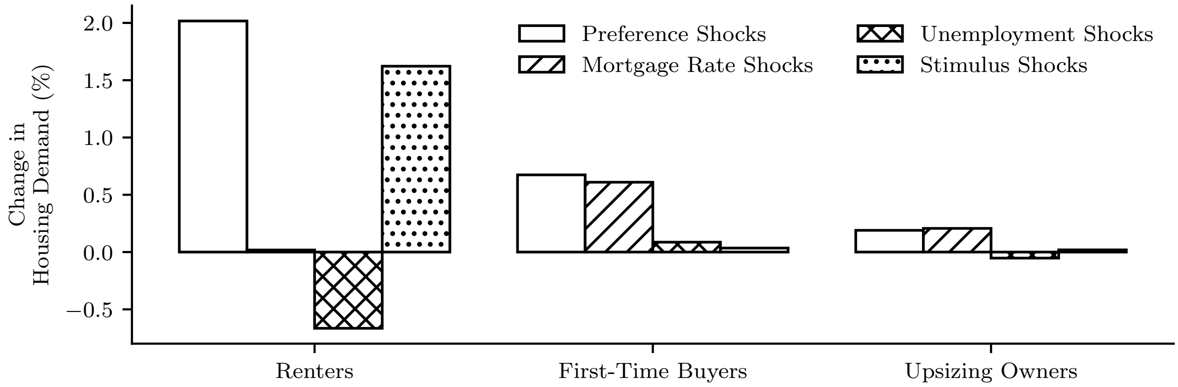
of a direct increase housing demand and looser borrowing constraints due to lower mortgage rates.

5.3. Sources of Housing Demand Across Households

We now study the sources of the changes in housing demand during the pandemic across households. First, we consider changes in demand along the extensive margin. Table 6 reports the proportion of households that are renters, first-time buyers, upsizing, downsizing, refinancing their mortgage, or not adjusting their housing portfolio. The first row refers to the steady state of the model, while all other rows refer to the 2020 period following the pandemic shocks in the partial equilibrium of the model. That is, we compute changes following the shocks without the subsequent effects of endogenous house price and rental price changes. Overall, our model suggests that the increase in housing demand is largely driven by first-time home buyers. However, an increase in the proportion of homeowners who are upsizing and small declines in the number of households downsizing also contribute to higher housing demand. In steady state, 1.9 percent of households become new homeowners in a given year. In contrast, 3.3 percent, 3.8 percent, and 2.5 percent of households become first-time buyers under the preference shock, mortgage rate shock, and stimulus shock, respectively. When the economy is hit by all shocks simultaneously, the first-time buyer share nearly triples relative to steady state, to 6 percent of households. In steady state, one percent of households upsize their house in a given year. This number rises to 1.6 percent following the preference shocks, and to 1.5 percent following the decline in mortgage rates. The number of households downsizing their houses falls from 0.6 percent in steady state to 0.4 percent following the preference shocks, and to 0.3 percent following the mortgage rate shocks.

Second, we consider changes in housing demand along the intensive margin. Figure 7 shows the average house sizes chosen by renters, first time buyers, and those upsizing their housing following the pandemic shocks relative to steady state. Again, we make use of the partial

Figure 7: Changes in House Size by Housing Tenure, Partial Equilibrium

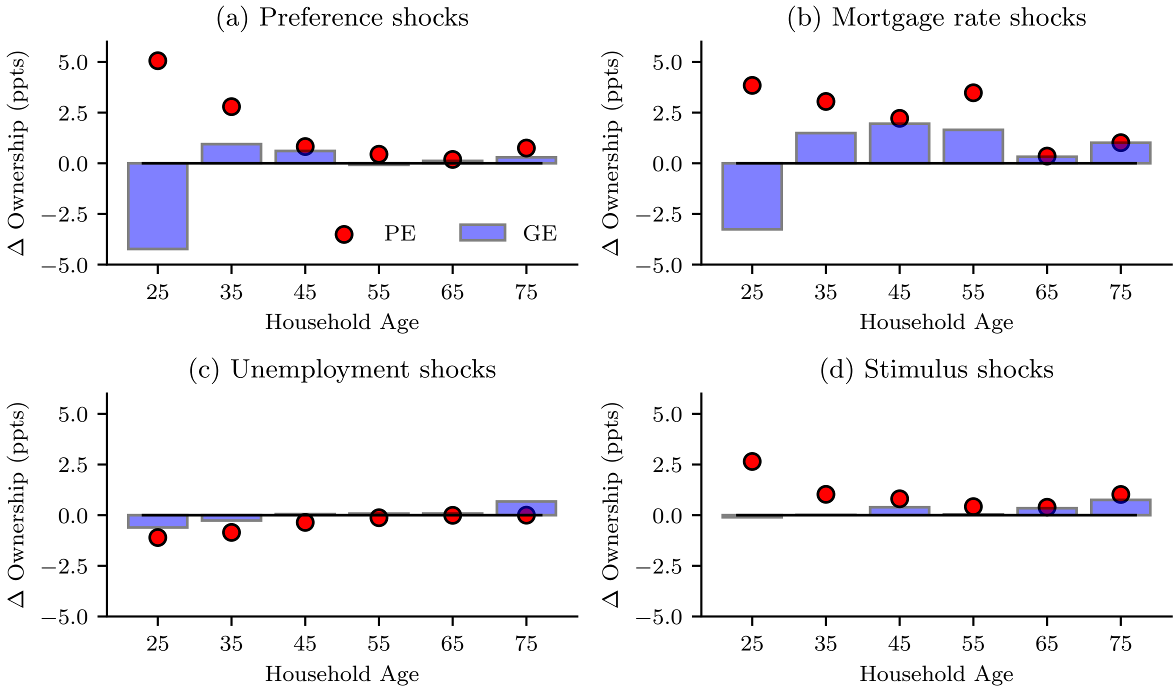


equilibrium of the model so that price changes do not obscure the underlying sources of the changes in demand. As expected, preference shocks lead to increases in demand for house size for households of all tenure types. The effects are largest for renters, next largest for first-time home buyers, and smallest for upsizing homeowners. Decreases in the mortgage rate have no effect on renters since they cannot borrow. However, the mortgage rate shocks have similar effects to stay-at-home shocks among first-time buyers and upsizing owners. Unemployment shocks and stimulus shocks have large effects on renters, but very limited effects on home buyers. This is because renters tend to be younger and have lower incomes than homeowners and therefore are much more sensitive to changes in income.

Our results so far suggest that the shift to consumption at home and fall in mortgage rates account for the bulk of the changes in housing demand during the pandemic. However, the endogenous responses of housing and rental prices to the pandemic shocks also affect housing demand. These price changes can offset the initial effects of the pandemic shocks, and may have large implications for the equilibrium distribution of housing demand. Figure 8 shows changes in homeownership rates relative to steady state across the age distribution of households. We show the effects of each of the four shocks in general equilibrium (blue bars) and in partial equilibrium (red dots). The difference between the partial equilibrium and general equilibrium effects of the pandemic illustrates how sensitive different households are to house price changes. Panel (a) shows the effect of the stay-at-home shocks alone. In partial equilibrium, young households experience a much larger increase in demand for homeownership than older households who are largely already homeowners. However, the large increase in house prices in general equilibrium more than offsets this effect so that households aged 25 to 35 experience an overall decline in the homeownership rate. This crowding out of young households in general equilibrium is to the benefit of households aged 35 to 55, who enjoy a moderate increase in homeownership.

Panel (b) of Figure 8 shows that mortgage rate shocks result in a similar partial equilibrium increase in homeownership for households aged 25 to 65. However, again, general equilibrium house price increases crowd out young households so that homeownership declines for those aged 25 to 35. Panel (c) shows that unemployment shocks have a small negative effect on homeownership for young households, but have essentially no effect on older households. Panel

Figure 8: homeownership Changes In Partial Equilibrium and General Equilibrium



(d) shows that the stimulus shocks have large partial equilibrium effects on the demand for homes among the youngest households. However, as with the other pandemic shocks, general equilibrium changes in house prices crowd out young home buyers whose homeownership rate is little changed on net.

6. Conclusion

The pandemic forced households to spend more time and money at home, which appears to have quantitatively important implications for housing market dynamics. We document a large and persistent increase in the share of household expenditure allocated to at-home consumption, and that more time spent at home was associated with faster house price growth during the pandemic. Our quantitative model suggests that around half of the increase in house prices over 2020 was due to these stay-at-home shocks, while lower mortgage rates accounted for around one-third of the increase. We find that young households and first-time home buyers drive the increase in underlying housing demand, but homeownership among young households declines during the pandemic due to the large equilibrium increase in house prices.

While our quantitative model provides a good fit to both pre-pandemic data and several important features of the pandemic, it remains limited in several respects. First, our model suffers from a similar problem facing most forward-looking models with asset prices: house price movements are front-loaded with respect to known future shocks. While house prices in our model jump in the first period of the pandemic before reverting to steady state, observed house price movements are more persistent. This shortcoming could potentially be overcome in a model with myopic households facing a sequence of unexpected shocks, with the addition of larger trading frictions, or with different household expectations formation. Second, we do not explicitly model the effects of working from home. While changing consumption patterns are one way to rationalize an increase housing demand, another is to consider the shift towards more time spent working from a home office, bedroom, or kitchen table. The sudden change in working patterns likely has more complex cross-sectional implications, since only some jobs can easily be carried out from home (Dingel and Neiman, 2020). We also leave this interesting issue for further research.

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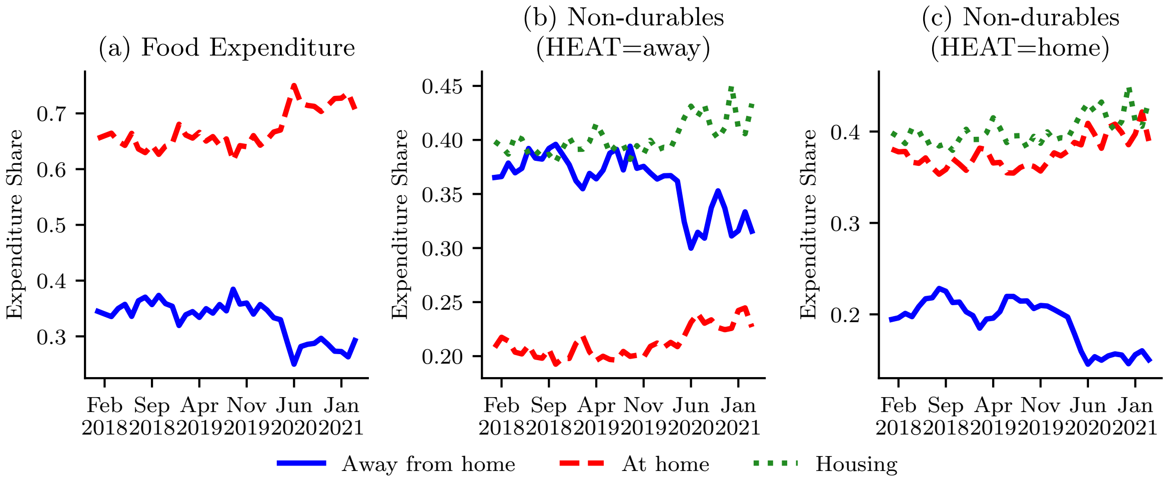
Appendix

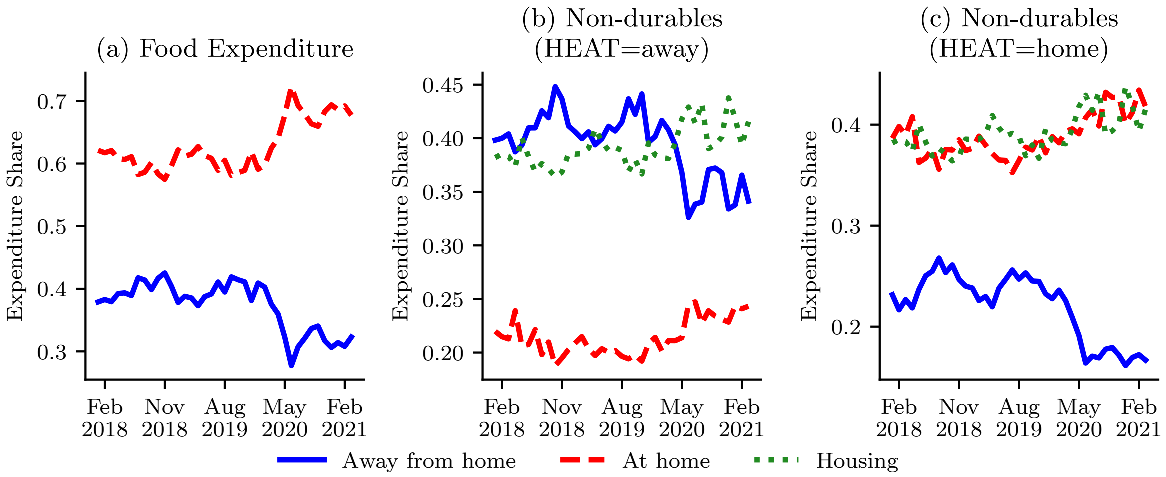
A. Additional Motivating Evidence

Figure A.1: Median Consumption Expenditure Shares



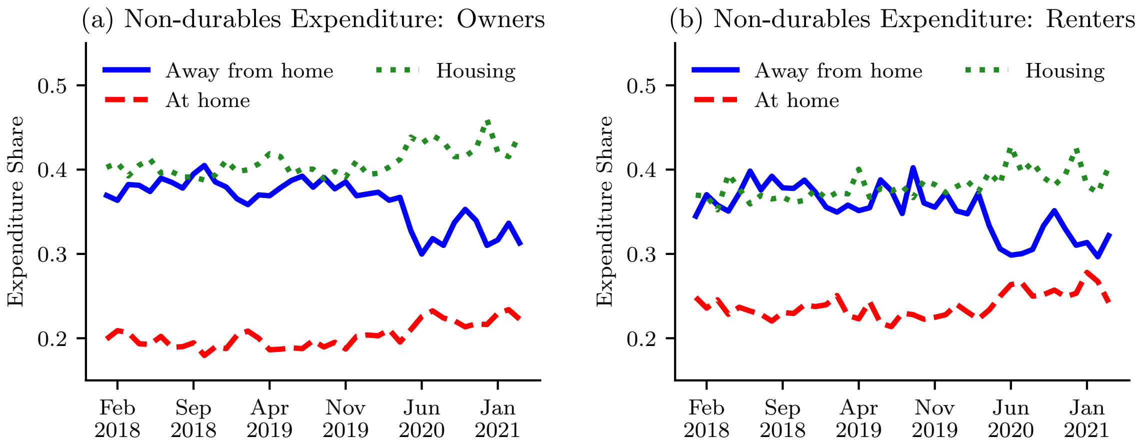
Notes: Median consumption expenditure shares for food only (a), non-durables and housing services ((b) and (c)). In panel (b) spending on health, education, alcohol, and tobacco is allocated to spending away from home. In panel (c) spending on health, education, alcohol, and tobacco is allocated to spending at home.
Source: Authors' calculations using data from the CEX.

Figure A.2: Aggregate Consumption Expenditure Shares



Notes: Aggregate consumption expenditure shares for food only (a), non-durables and housing services ((b) and (c)). In panel (b) spending on health, education, alcohol, and tobacco is allocated to spending away from home. In panel (c) spending on health, education, alcohol, and tobacco is allocated to spending at home.
Source: Authors' calculations using data from the CEX.

Figure A.3: Median Consumption Expenditure Shares for Homeowners and Renters



Notes: Median consumption expenditure shares non-durables and housing services. Panel (a) reports shares for homeowners, panel (b) reports shares for renters. In each panel, spending on health, education, alcohol, and tobacco is allocated to spending away from home.
Source: Authors' calculations using data from the CEX.

B. Additional Empirical Results

Table B.7: House Price Response to Changes in Local Mobility: Alternative Instruments

	Real 12-month house price growth							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Mobility: Time At Home	0.457***		0.507***		0.127***		0.827***	
	(0.116)		(0.088)		(0.029)		(0.244)	
Δ Mobility: Visitis to Retail, Recreation		−0.128***		−0.151***		−0.052***		−0.286***
		(0.036)		(0.026)		(0.013)		(0.101)
Δ Employment	0.220***	0.108***	0.249***	0.136***	0.028	0.017	0.435***	0.299**
	(0.064)	(0.040)	(0.049)	(0.031)	(0.025)	(0.024)	(0.143)	(0.127)
ln(Population)	0.006***	0.004***	0.006***	0.003***	0.008***	0.007***	0.005**	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)
ln(Income Per Capita)	−0.027***	−0.018***	−0.029***	−0.020***	−0.015***	−0.014***	−0.041***	−0.028**
	(0.005)	(0.005)	(0.005)	(0.006)	(0.004)	(0.005)	(0.010)	(0.012)
Land Unavailability	−0.009	−0.004	−0.008	−0.002	−0.014**	−0.011*	−0.003	0.011
	(0.006)	(0.008)	(0.006)	(0.007)	(0.006)	(0.007)	(0.008)	(0.013)
$\mathbb{1}(t \leq$June 2020)	−0.009***	−0.009***	−0.009***	−0.010***	−0.007***	−0.008***	−0.011***	−0.013***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.003)	(0.004)
Observations								
Total	13,890	13,890	13,890	13,890	13,890	13,890	13,890	13,890
Counties	1,442	1,442	1,442	1,442	1,442	1,442	NULL	1,442
Method	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Instrument	Deaths	Deaths	Cases	Cases	Lockdown	Lockdown	Vote Share	Vote Share
State Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
State-Clustered Standard Errors	Y	Y	Y	Y	Y	Y	Y	Y
First Stage F-statistic	15.16	34.85	6.20	8.18	440.76	186.17	4.24	9.53

Notes: All specifications using instruments for mobility constructed from the share of workers most easily able to work from home interacted with state-level measures of pandemic intensity over time. Columns (1) and (2) use the baseline instrument that interacts WFH with the confirmed number of COVID deaths over time. Columns (3) and (4) use an instrument that interacts WFH with the confirmed number of COVID cases over time. Columns (5) and (6) use an instrument that interacts WFH with the stringency of lockdowns over time. Columns (7) and (8) use an instrument that interacts Republican vote shares in the 2016 presidential election with the confirmed number of COVID deaths over time. All standard errors and first-stage F-statistics clustered at the state level.

Sources: Authors' calculations using data from BLS, Census, Dingel and Neiman (2020), MIT Election Data and Science Lab (2018), Google Mobility Reports, Hale et al. (2021), Lutz and Sand (2019), Zillow

Table B.8: House Price Response to Changes in Local Mobility: Alternative Specifications

	Real 12-month house price growth			
	(1)	(2)	(3)	(4)
Δ Mobility: Time At Home	0.457***	0.789*	0.541*	0.581***
	(0.116)	(0.429)	(0.300)	(0.137)
Δ Employment	0.220***	0.307*	0.171***	0.283***
	(0.064)	(0.168)	(0.051)	(0.080)
ln(Population)	0.006***	0.009***	0.010***	0.006***
	(0.001)	(0.003)	(0.003)	(0.002)
ln(Income Per Capita)	−0.027***	−0.034**	−0.027***	−0.028***
	(0.005)	(0.015)	(0.010)	(0.006)
Land Unavailability	−0.009	−0.002	−0.011	−0.005
	(0.006)	(0.008)	(0.008)	(0.006)
$\mathbb{1}(t \leq$June 2020)	−0.009***	−0.013***		−0.009***
	(0.002)	(0.002)		(0.002)
$\mathbb{1}(t \geq$Jan 2021)		0.006		
		(0.010)		
Observations				
Total	13,890	24,879	7,824	12,979
Counties	1,442	1,453	1,392	1,354
Method	2SLS	2SLS	2SLS	2SLS
Specification	Baseline	2020-2021	Jun-Dec 2020	Excl. NY, WA
State Fixed Effects	Y	Y	Y	Y
State-Clustered Standard Errors	Y	Y	Y	Y
First Stage F-statistic	15.16	3.85	3.40	7.12
Adjusted R-squared	0.15	0.06	0.26	0.04

Notes: All specifications using instruments for mobility constructed from the share of workers most easily able to work from home (Dingel and Neiman, 2020) interacted with state-level confirmed COVID deaths over time. Column (1) is the baseline specification. Column (2) uses data from both 2020 and 2021. Column (3) restricts the sample from June to December 2020. Column (4) excludes data from the states of New York and Washington. All standard errors and first-stage F-statistics clustered at the state level.
Sources: Authors' calculations using data from BLS, Census, Dingel and Neiman (2020), Google Mobility Reports, Hale et al. (2021), Lutz and Sand (2019), Zillow

Table B.9: Rental Rate Response to Changes in Local Mobility

	Real 12-month rental rate growth			
	(1)	(2)	(3)	(4)
Δ Mobility: Time At Home	0.088***		0.011	
	(0.025)		(0.513)	
Δ Mobility: Visitis to Retail, Recreation		−0.017		−0.002
		(0.012)		(0.115)
Δ Employment	−0.007	−0.042*	−0.062	−0.066
	(0.025)	(0.025)	(0.389)	(0.203)
ln(Population)	−0.006**	−0.006**	−0.005**	−0.005
	(0.002)	(0.003)	(0.002)	(0.003)
ln(Income Per Capita)	−0.032***	−0.030***	−0.029	−0.028**
	(0.004)	(0.004)	(0.025)	(0.011)
Land Unavailability	−0.042*	−0.044*	−0.045	−0.045
	(0.025)	(0.025)	(0.042)	(0.037)
$\mathbb{1}(t \leq$June 2020)	−0.006	−0.005	−0.005	−0.005
	(0.004)	(0.004)	(0.007)	(0.006)
Observations				
Total	2,421	2,421	2,421	2,421
Counties	221	221	221	221
Method	OLS	OLS	2SLS	2SLS
State Fixed Effects	Y	Y	Y	Y
State-Clustered Standard Errors	Y	Y	Y	Y
First Stage F-statistic	–	–	5.60	48.14
Adjusted R-squared	0.18	0.18	0.18	0.18

Notes: Columns (1) and (2) are OLS regressions, and Columns (3) and (4) are 2SLS regressions. The instrument for mobility is the interaction between the county-level share of workers most easily able to work from home with state-level confirmed COVID deaths over time. All specifications include county-level controls for employment growth rates, population, per-capita income, land unavailability, in addition to a dummy for months prior to July 2020, and state fixed effects. All standard errors and first-stage F-statistics clustered at the state level.
Sources: Authors' calculations using data from BLS, Census, Dingel and Neiman (2020), Google Mobility Reports, Hale et al. (2021), Lutz and Sand (2019), Zillow

C. Additional Model Details

C.1. Static Model

In this section we use a simple one-period model with the preferences defined in Section 3 to analytically explore the effect of stay-at-home shocks on housing demand and house prices. As in the quantitative model, assume that utility is a CES composite of away-from-home consumption and the home bundle:

$$u(c_a, c_h, s) = \left[\alpha c_a^{1-\vartheta} + (1-\alpha) x_h(c_h, s)^{1-\vartheta}\right]^{\frac{1}{1-\vartheta}}$$

Since this is a one period model, we drop the outer CRRA structure. Again, the home bundle is a Cobb-Douglas combination of consumption at home c_h and housing services s:

$$x_h = c_h^{\phi} s^{1-\phi}.$$

The static budget constraint is:

$$c_a + c_h + Ps = W$$

where c_a and c_h have prices normalized to one, P is the price of housing services, and W is available resources. The first order conditions of the household problem yield the demand functions:

$$c_a = \frac{\Omega W}{1+\Omega}, \quad c_h = \frac{\phi W}{1+\Omega}, \quad s = \frac{1}{P}\frac{(1-\phi)W}{1+\Omega}$$

where $\Omega = \phi \left(\frac{\alpha}{\phi(1-\alpha)}\right)^{1/\vartheta} \left(\frac{\phi P}{1-\phi}\right)^{(1-\phi)(1/\vartheta-1)}$.

A stay-at-home pandemic shock is modelled as a decline in preferences for consumption away from home α or, equivalently, as an increase in the preference to consume at home $(1-\alpha)$. In our simple setup, this change in preferences results in both an increase in demand for non-durable consumption at home c_h and housing services s. With fixed housing supply in the short-run, the price of housing services increases with the decline in α. We formalize this argument in a simple proposition:

Proposition 1. Suppose $\alpha, \phi \in (0,1)$ and that the supply of housing is fixed. If the elasticity of substitution satisfies $1/\vartheta > 1$, then $\frac{\partial P}{\partial \alpha} < 0$.

Proof. Suppose the supply of housing is fixed at $\bar{s}$. We can rewrite the demand function for housing services as:

$$P = \frac{1}{\bar{s}}\frac{(1-\phi)W}{1+\Omega}$$

Via the Implicit Function Theorem:

$$\frac{\partial P}{\partial \alpha} = \frac{-\frac{\partial \Omega}{\partial \alpha}\frac{1}{\bar{s}}\frac{(1-\phi)W}{(1+\Omega)^2}}{1+\frac{\partial \Omega}{\partial P}\frac{1}{\bar{s}}\frac{(1-\phi)W}{(1+\Omega)^2}} = \frac{-\frac{\partial \Omega}{\partial \alpha}\frac{P}{(1+\Omega)}}{1+\frac{\partial \Omega}{\partial P}\frac{P}{(1+\Omega)}}$$

where the second equality uses the housing services demand function. The partial derivative in the denominator is

$$\frac{\partial \Omega}{\partial \alpha} = \frac{1}{\vartheta} \frac{\Omega}{\alpha(1-\alpha)}$$

and the partial derivative in the numerator is

$$\frac{\partial \Omega}{\partial P} = \frac{(\frac{1}{\vartheta} - 1)(1-\phi)\Omega}{P}.$$

Then the price derivative is:

$$\frac{\partial P}{\partial \alpha} = \frac{-\frac{1}{\vartheta}\frac{P}{\alpha(1-\alpha)}}{(\frac{1}{\vartheta} - 1)(1-\phi) + \Omega^{-1}}$$

Under the assumptions that $\alpha, \phi \in (0,1)$ and $\frac{1}{\vartheta} > 1$, the denominator is positive, and therefore

$$\frac{\partial P}{\partial \alpha} < 0$$

□

That is, if the home consumption bundle and away-from-home consumption are substitutes, a decline in the relative taste for away-from-home consumption α will lead to an increase in the price of housing. Our quantitative model expands on this simple setup, adding realism to the simple framework described here. These additional features allow us to assess the overall importance of the stay-at-home channel for explaining the growth in house prices during the COVID-19 pandemic.

C.2. Household First Order Conditions

Here we describe the optimality conditions for households that own houses or are adjusting their housing stock. This characterization of the optimal decisions differs from the first order conditions described in Section C.1. In the simple model households make frictionless and continuous house size choices, whereas the renters and homeowners in Section 3.2 choose house sizes from a discrete grid subject to costs.

Consider a household that has already chosen a house or rental size $\tilde{h}$. Denote by $\tilde{x}$ the available cash on hand after liquid asset choices a' and any rental payments or housing adjustment costs. The first order conditions with respect to consumption away from home c_a and at home c_h yield:

$$c_a = \left(\frac{\alpha}{\phi(1-\alpha)}\right)^{\frac{1}{\vartheta}} c_h^{\phi + \frac{1}{\vartheta}(1-\phi)} \tilde{h}^{(1-\frac{1}{\vartheta})(1-\phi)}$$

Combining with the expenditure constraint and definition of cash on hand yields

$$\left(\frac{\alpha}{\phi(1-\alpha)}\right)^{\frac{1}{\vartheta}} c_h^{\phi + \frac{1}{\vartheta}(1-\phi)} \tilde{h}^{(1-\frac{1}{\vartheta})(1-\phi)} + c_h = \tilde{x}$$

We solve this non-linear equation to find the choice of home goods c_h, and in combination with the budget constraint recover the solution for away goods c_a. The solution to the consumption choices then only depends on the current state vector, the house size choice $\tilde{h}$, and the liquid asset choice a'.

C.3. Equilibrium

Definition. A stationary recursive competitive equilibrium is a set of value functions $\{V_j(\mathbf{s}), V_j^R(\mathbf{s}), V_j^N(\mathbf{s}), V_j^A(\mathbf{s})\}$ and decision rules $\{c_{a,j}(\mathbf{s}), c_{h,j}(\mathbf{s}), s_j(\mathbf{s}), h_j'(\mathbf{s}), a_j'(\mathbf{s})\}$ for all j; prices $\{P_h, P_r\}$; fixed housing supply $\bar{H}$; and a distribution of households over idiosyncratic states $\Phi_j(\mathbf{s})$ for all j such that:

1. Given prices, $\{V_j(\mathbf{s}), V_j^R(\mathbf{s}), V_j^N(\mathbf{s}), V_j^A(\mathbf{s})\}$ solve the household's problem, with associated decision rules $\{c_{a,j}(\mathbf{s}), c_{h,j}(\mathbf{s}), s_j(\mathbf{s}), h_j'(\mathbf{s}), a_j'(\mathbf{s})\}$ for all j.

2. Given $P_h = P_h'$, the rental price P_r is given by the user-cost formula in Equation (2).

3. The total housing stock is given by the total demand for owner-occupied housing and rental units:

$$\bar{H} = \sum_{j=1}^{J} \int_{\mathbf{s}} h_j'(\mathbf{s}) d\Phi_j(\mathbf{s}) + \sum_{j=1}^{J} \int_{\mathbf{s}} s_j(\mathbf{s}) d\Phi_j(\mathbf{s})$$

4. The distribution of households over idiosyncratic states Φ_j is given by the law of motion:

$$\Phi_{j+1}(\mathbf{s}') = \int_{\mathbf{s}} Q_j(\mathbf{s}, \mathbf{s}') d\Phi_j(\mathbf{s})$$

   for $j < J$ and where Q_j is a function that defines the probability that an age-j household with state $\mathbf{s}$ transitions to the state $\mathbf{s}'$ at age $j+1$ and is induced by the age-j decision rules and the exogenous processes for labor income and unemployment.

C.4. Solving the Model

In the initial steady state we normalize the house price $P_h = 1$. The rental rate is then given by the user-cost equation (2). Given the house price and rental rate, we then solve the household's problem via value function iteration, taking prices as given, and compute the stationary distribution using the histogram method of Young (2010). The rental market clears by assumption because the rental sector supplies any quantity of units at the market rental rate. We then infer the level of housing supply $\bar{H}$ from the market clearing condition in the equilibrium definition of Section C.3.

In all of our dynamic model experiments we keep the aggregate housing stock fixed at its level in the stationary distribution. However, the composition of housing between owner-occupied and rental units is allowed to vary as demand conditions change.[35] All of our experiments are computed as perfect-foresight transition paths, where we solve for the sequence of house prices $\{P_{h,t}\}_{t=1}^{t=T}$ such that the overall demand for housing equals the fixed housing stock in each period.

C.5. Additional Model Results

[35] The assumption of a housing stock flexibly composed of owner-occupied and rental units is a common one in dynamic models of the housing market; see for example: Kaplan, Mitman, and Violante, 2020a and Karlman, Kinnerud, and Kragh-Sorensen, 2021.

Figure C.1: Impulse Responses: Robustness to Shock Persistence

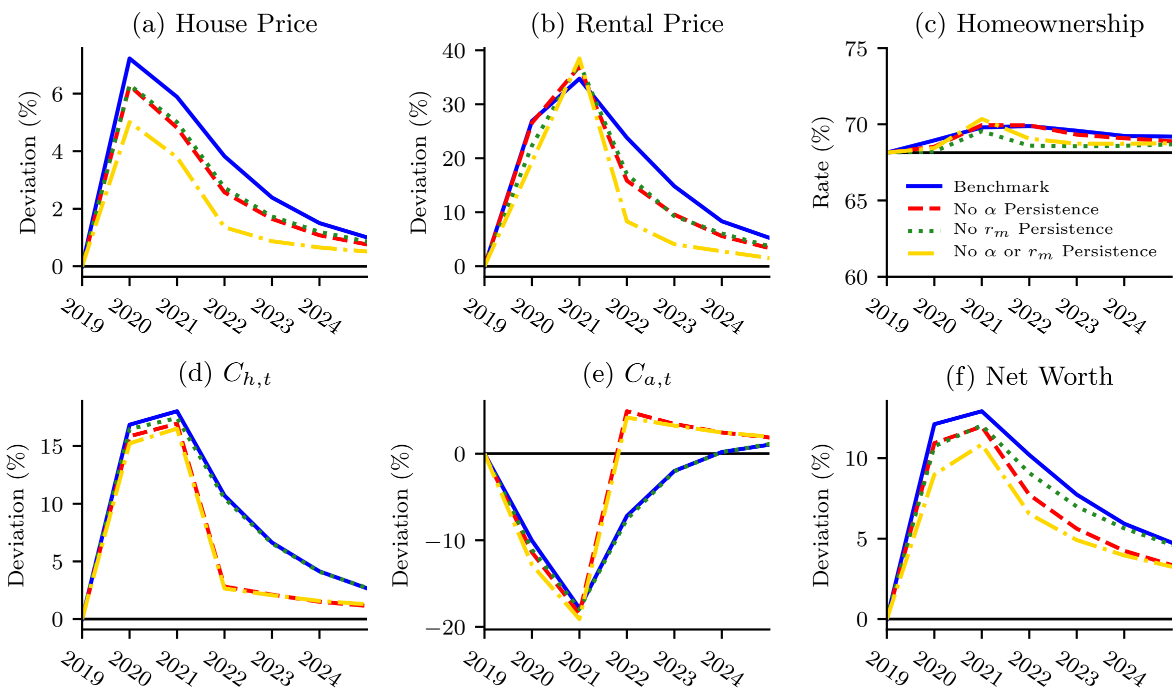


Figure C.2: Impulse Responses: Robustness to Housing and Rental Market Segmentation