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Stuck at home: Housing demand during the COVID-19 pandemic

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A B S T R A C T

The COVID-19 pandemic induced an increase in both the amount of time that households spend at home and the share of expenditures allocated to at-home consumption. These changes coincided with a period of rapidly rising house prices. We interpret these facts as the result of stay-at-home shocks that increase demand for goods consumed at home as well as the homes that those goods are consumed in. We first test the hypothesis empirically using US cross-county panel data and instrumental variables regressions. We find that counties where households spent more time at home experienced faster increases in house prices. We then study various pandemic shocks using a heterogeneous agent model with general equilibrium in housing markets. Stay-at-home shocks explain around half of the increase in model house prices in 2020. Lower mortgage rates explain around one third of the price rise, while unemployment shocks and fiscal stimulus have relatively small effects on house prices. We find that young households and first-time home buyers account for much of the increase in housing demand during the pandemic, but they are largely crowded out of the housing market by the equilibrium rise in house prices.

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.[2] 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 Fig. 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.[3] 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 modeling 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

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2 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.

3 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 et al. (2021).

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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 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 consumption, 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.[4] These changes in consumption patterns are also reflected in changes in the time that households spent at home and away from home. Drawing on measures of household mobility from Google Mobility Reports, we show that households spent around 10 percent more time at home on average during the pandemic in 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 visits 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. 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 the 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 the house price increase, while unemployment shocks and fiscal stimulus have relatively small effects on house prices. We show that much of the increase in housing demand is driven by first-time home buyers, with some additional effect due to more existing homeowners upsizing and fewer existing homeowners downsizing. 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 towards lower-density suburban areas during the pandemic (Gupta et al., 2022; Liu and Su, 2021; Ramani and Bloom, 2021; Guglielminetti et al., 2021). Both Gupta et al. (2022) 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 with which employees can work from home (WFH). Delventhal et al. (2020) and Davis et al. (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 urban and real estate literature cited above. 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

[4] 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 Online Appendix A for details.

[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).

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.

The most closely related study to our own is in Diamond et al. (2022). They model the endogenous effect of a decline in consumption of "in-person" goods on household incomes, and the subsequent spillover to the housing market. They show that absent government fiscal policies to support household incomes and temporarily delay mortgage foreclosures, aggregate income and consumption would have fallen, house prices would have declined, and mortgage defaults would have increased. Diamond et al. (2022) model the COVID-19 shock as a shift in preferences away from "in-person" goods, which is similar to our choice to model the shock as a shift in preferences from away-from-home consumption and towards at-home consumption. The primary difference between the two papers is that we model housing services as complementary to at-home consumption which generates strong co-movement between the rise in demand for consuming at home and the consumption of housing services. Other smaller differences are that we abstract from mortgage default, the financial sector, and general equilibrium in goods markets, and Diamond et al. (2022) adopt a two-agent spender-saver model while we employ a life-cycle heterogeneous agent model.

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 et al., 2020), sectoral demand or supply shocks (Danieli and Olmstead-Rumsey, 2021; Faria-e-Castro, 2021; Guerrieri et al., 2022; 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 et al., 2020; Faria-e-Castro, 2021; Kaplan et al., 2020b). While several of these papers build heterogeneous agent models to understand the role of the wealth distribution in the pandemic (for example, Carroll et al., 2020; Nakajima, 2020; Kaplan et al., 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 et al., 2020a; Guren et al., 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.

We then study the relationship between house prices and time use in a county-month panel. To address concerns about endogeneity, we construct a shift-share instrument for time spent at home by interacting a county-level measure of the share of employment that could be carried out at home before the pandemic (Dingel and Neiman, 2020) with time-varying state-level measures of pandemic intensity. Our two-stage least squares estimates imply that counties with larger increases in time spent at home experienced significantly larger increases in house prices.

2.1. Aggregate trends during the pandemic

Fig. 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 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]

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 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

[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.

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

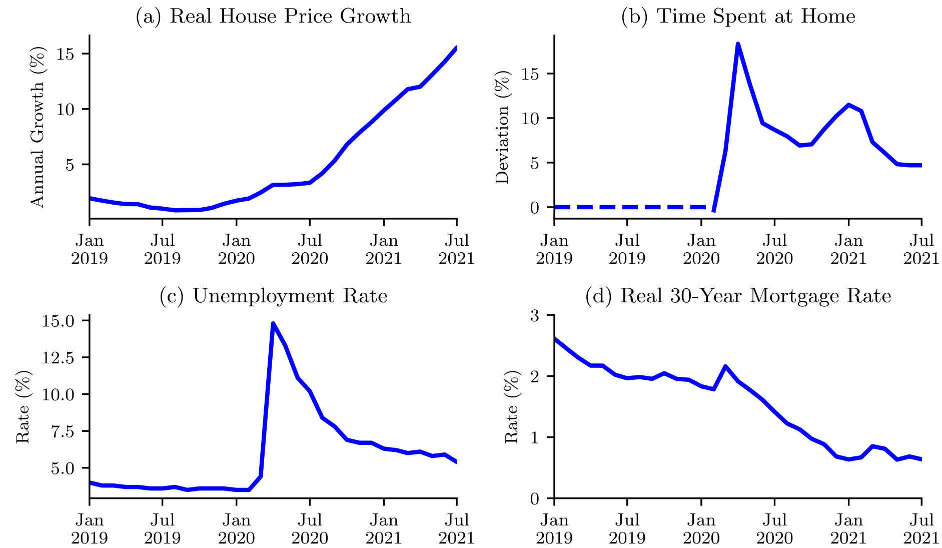

Fig. 1. Evolution of macroeconomic aggregates during the pandemic. *Notes:* Real house price growth (panel a) is the 12-month growth rate in the S&P/Case-Shiller U.S. National Home Price Index minus annual core CPI inflation. Mobility away from home (panel b) is time spent away from home from Google 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.

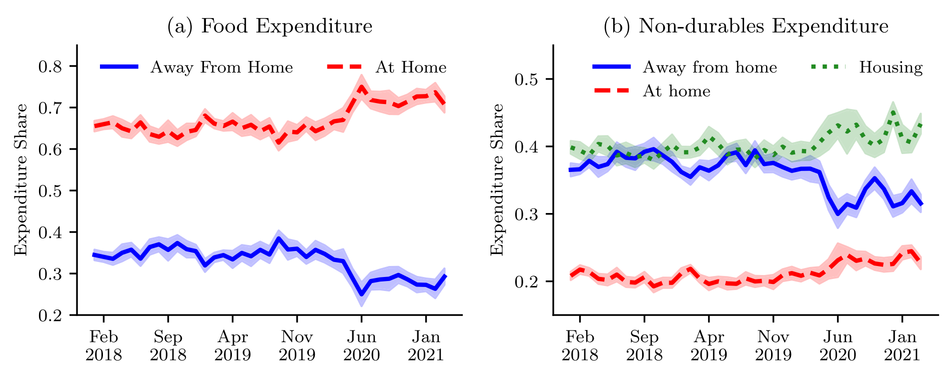

Fig. 2. Median consumption expenditure shares. *Notes:* Median consumption expenditure shares for (a) food only, and (b) non-durables and housing services. Shaded regions show 95% confidence intervals for the median expenditure shares, computed via bootstrapping. In panel (b) spending on alcohol, tobacco, 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.

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 Online 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.

Fig. 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 percentage points in 2020. Panel (b) shows the shares of non-durables expenditure allocated to the at home, away from home, and housing services categories. 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 percentage points, the housing services share rose by 2.0 percentage points, while the away-from-home share of consumption fell by 3.9 percentage points.

In Online 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, and tobacco are allocated to consumption at home. In that case, the median non-durables share spent at home rises by 2.7 percentage points and the share spent away from home falls by 4.3 percentage points in 2020. Since these changes in consumption shares are similar to those reported in Fig. 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 film and concert tickets), and

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.

transport. Online Appendix A.2 reports aggregate consumption shares, which exhibit very similar patterns to the median consumption shares.

Finally, Figure A.3 in Online 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 percentage points, the away-from-home share falls by 4 percentage points, and the housing services share rises by 2.1 percentage points. For renters, the at-home consumption share rises by 1.6 percentage points, the away-from-home share falls by 4 percentage points, and the housing services share rises by 2.3 percentage points. 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 at home or larger decreases in 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. The Google Mobility Reports data provides changes in household mobility relative to average mobility during a baseline 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.

The Google Mobility Reports data are informative about the composition of consumption across at-home and away-from-home goods. Our first measure, time spent at home, is likely to be associated with both home production and home consumption. While time spent consuming at home is likely to be correlated with the amount of home consumption, time spent working from home is also likely to be associated with eating, exercising, and consuming entertainment at home.[11] Our second measure – visits to retail and recreation locations – is directly related to consumption outside of the home.

Our data on house prices are from the Zillow Home Value Index, provided by the real estate company Zillow.[12] 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.

Fig. 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.

2.4. Two stage least squares estimates

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, 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.

The data used to estimate Eq. (1) come from several sources. As above, house price data are from Zillow and household mobility data comes from Google Mobility Reports where the two measures are time spent at home and number of visits to retail and recreation locations. We then use several different data sources to produce control variables. 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 (2022).[13] 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 $\alpha_{t \leq June2020}$ indicating the months in the first half of 2020 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 Fig. 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 outbreaks or lockdowns may have had larger declines in income that suppressed house prices. Since bigger outbreaks and stricter 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 Eq. (1) to be biased towards zero.

We address this endogeneity problem by estimating Eq. (1) via two-stage-least-squares using a shift-share style instrument for household mobility.[14] To construct our instrument, we interact the local share of employment that can feasibly be carried out at home with a time-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

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

[11] Many of these "out-of-the-home" expenses are work-related. As noted in Aguiar and Hurst (2013), work-related expenses, like food away from home and transportation, decline significantly in retirement.

[12] 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.

[13] Lutz and Sand (2022) 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).

[14] For recent discussions of shift-share instruments see Goldsmith-Pinkham et al. (2020).

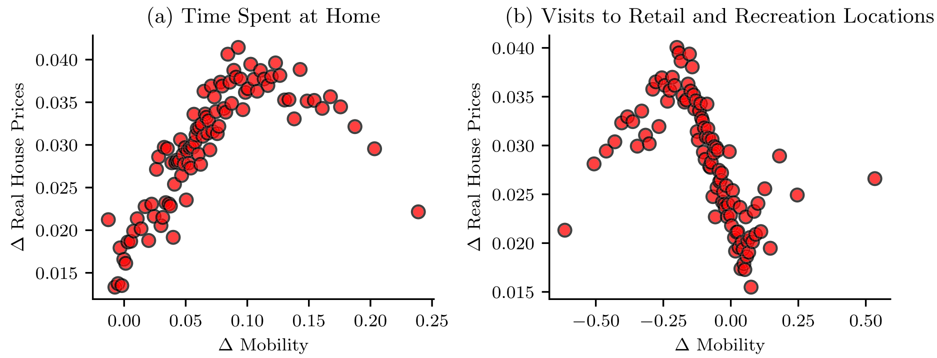

Fig. 3. Changes in mobility and house prices. *Notes:* Binned scatter plots of changes in household mobility against annual real house price growth. Panel (a) sorts on percentiles of changes in average duration at own place of residence. Panel (b) sorts on percentiles of changes in average duration away 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.

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.[15] 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).[16]

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.[17] 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 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. We also include state-level fixed effects, which ensures that we are comparing counties within states facing the same level of pandemic intensity. Finally, since the time series variation in the instrument is the same across counties within a state we cluster standard errors at the state level.

Table 1 reports our OLS and 2SLS estimates of Eq. (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

Table 1
House price response to changes in local mobility.
Source: Authors' calculations using data from BLS, Census, Dingel and Neiman (2020), Google Mobility Reports, Hale et al. (2021), Lutz and Sand (2022), Zillow.

	Real 12-month house price growth			
	(1)	(2)	(3)	(4)
Δ Time at home	0.125***		0.457***	
	(0.015)		(0.116)	
Δ Visits 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	1442	1442	1442	1442
Method	OLS	OLS	2SLS	2SLS
State fixed effects	Y	Y	Y	Y
State-clustered standard errors	Y	Y	Y	Y
First stage F-statistic	–	–	15.21	34.96
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.

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 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.

We also consider several robustness checks of our main empirical results. First, in Table B.7 in Online Appendix B, we re-estimate our 2SLS regressions using alternative versions of the shift-share instrument

[15] 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.

[16] 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.

[17] This is the exogeneity assumption for shift-share instruments discussed in Goldsmith-Pinkham et al. (2020).

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 (0.507 and −0.151, respectively) 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 (0.127 and −0.052, respectively) 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).[18] These estimates (0.827 and −0.286, respectively) are larger than but not statistically significantly different from our baseline results.

Second, in Table B.8 in Online Appendix B we investigate whether our results are sensitive to other controls and samples. Column (1) repeats our baseline 2SLS results for the time spent at home variable. Column (2) includes an additional control for changes in time spent at the workplace, where we take the county-level average of deviations from the baseline period for the six months ending in March 2022. Our inclusion of this variable is an attempt to control for medium- to long-run changes in willingness to work from home. The estimated coefficient of 0.464 is not statistically different from our baseline estimate. In Column (3) we adjust the sample to include data from both 2020 and 2021. In this specification we also include a dummy variable for observations in the year 2021. The 2SLS estimate of 0.789 is larger than but not statistically significantly different from our baseline estimate. In Column (4) we only use data from the second half of 2020, by which time COVID-19 had spread throughout the US. This specification produces very similar results (0.541) to our baseline estimates. Finally, in Column (5) we again use data from 2020 but exclude data from New York and Washington, since these states were especially hard hit early in the pandemic when the shock was relatively new and potentially more disruptive. With an estimated coefficient of 0.581 we again find no statistically significant difference from our baseline estimates.

Third in Table B.9 in Online Appendix B we consider whether rents respond to stay-at-home shocks in a similar way to house prices.[19] We might expect that the increase in demand for housing applies to both owned and rented houses. We find that the direction of the response of rents to stay-at-home shocks is similar to house prices, although the magnitude of 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 $j \in [1, \dots, J]$. 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:

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

where $u(\cdot)$ is the flow utility function, $v(\cdot)$ 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 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.

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 α is the relative taste for consumption away from home, $1/\vartheta$ is the intratemporal elasticity of substitution between away-from-home consumption and the home bundle, and $1/\sigma$ is the intertemporal elasticity of substitution.[20] The home bundle x_h is a Cobb–Douglas combination of at-home consumption c_h and housing services s:

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

Our main pandemic experiment in Section 5 is a stay-at-home shock generated 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 Online 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:

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

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

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

where unemployed households find a job with a constant probability f, but the job separation rate for employed households d_j depends on their

[18] Engle et al. (2020) document that counties with higher Republican vote shares had smaller reductions in household mobility during the pandemic.

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

[20] In a multi-sector New Keynesian model, Guerrieri et al. (2022) show that sectoral supply shocks can have spillover effects on demand when the intertemporal elasticity of substitution is larger than the intratemporal 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.

age.[21] 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 are

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

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 a maintenance cost δ each period, which is 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 the purchase of houses 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 modeled in the literature.[22] 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:

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

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 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:

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

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):

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

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

[21] 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.

[22] We assume one-period mortgage debt for tractability, but recent papers have studied models with long-term mortgage contracts. See, for example, Garriga et al. (2017), Kaplan et al. (2020a), Boar et al. (2020), Karlman et al. (2021).

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:

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

The problem for a non-adjusting household is:

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

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:

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

The function $\boldsymbol{\psi}(a, a', h, h')$ 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):

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

The function $\mathbb{1}_{h' \ne h}$ is an indicator for new house purchases, and is equal to one whenever a household changes the size of their existing housing stock.

3.3. Equilibrium and computational details

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

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 et al. (2020a)
Productivity persistence	ρ_z	0.97	Kaplan et al. (2020a)
Retirement replacement rate	ω_{ret}	0.50	Díaz and Luengo-Prado (2008)
Unemployment replacement rate	ω_u	0.50	Krueger et al. (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 et al. (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

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 is defined below.[23]

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 determined by the user-cost formula in Eq. (2).
3. The total housing stock is equal to 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.

We compute the stationary equilibrium numerically. In the initial steady state we normalize the house price $P_h = 1$. The rental rate is then given by the user-cost Eq. (2). Given the house price and rental rate, we then solve the household's problem via value function iteration 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. In all of our dynamic model experiments we keep the aggregate housing stock fixed at $\bar{H}$. However, the composition of housing between owner-occupied and rental units is allowed to vary as demand conditions change.[24] 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.

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.

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 $\sigma = 2$ implying an intertemporal elasticity of substitution of 0.5, which is standard in the literature.

We set the intratemporal 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. Piazzesi et al. (2007) estimate an intratemporal elasticity of substitution between non-durable consumption and housing services of around 1.25 using aggregate data. Since the home bundle in our model includes non-durable at-home consumption goods it is likely to be more substitutable with away-from-home goods than total non-durables are with housing services (i.e. as in the estimates of Piazzesi et al., 2007). This suggests we should use an intratemporal elasticity larger than 1.25. Papers in the home production literature that estimate elasticities between the home and market sectors report values in the range of 1.7–2.5. For example, Benhabib et al. (1991) and McGrattan et al. (1997) estimate elasticities of substitution between home and market produced goods of around 2.5 and 1.75, respectively. Aguiar and Hurst (2007) and Nevo and

[23] 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. See Diamond et al. (2022) for a more complete general equilibrium analysis.

[24] The assumption of a housing stock flexibly composed of different sizes of owner-occupied and rental units is common; see for example Kaplan et al. (2020a) and Karlman et al. (2021). Alternatively, we could fix the composition of house sizes and allow the relative price of each house size to adjust to clear separate housing markets. Landvoigt et al. (2015) provide an example of such a model. We abstract from this complication to maintain computational tractability.

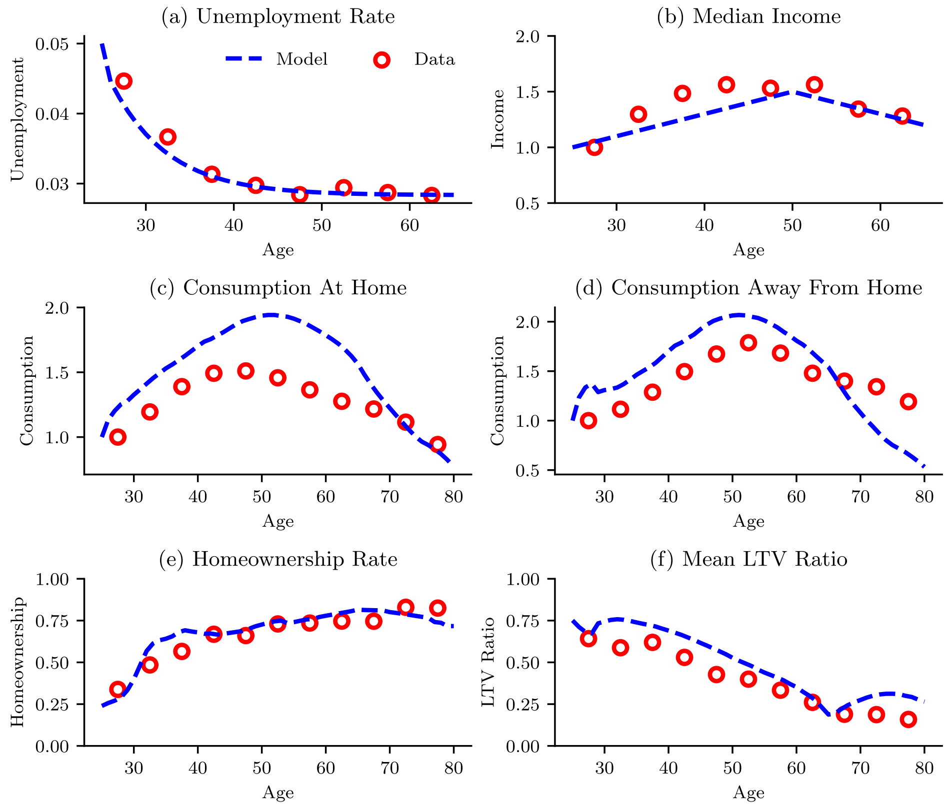

Fig. 4. Model fit to life-cycle statistics. *Notes:* All statistics in the data computed for five-year age bins starting from age 25. Panels (b), (c), and (d) normalize both model and data to one at the first age. Panel (f) reports the average LTV ratio for all homeowners.
Source: Authors' calculations using data from the CEX, CPS, and SCF.

Wong (2019) report estimated elasticities of substitution between time and market goods used in home production of 1.7–2.2. Although we do not explicitly model time use or home production, these estimates are instructive because there is likely a high correlation between home consumption of market goods (which we model) and home production.

Endowments. We take the parameters that govern the idiosyncratic income process from Kaplan et al. (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 simple tent shape, following (Ma and Zubairy, 2021):

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

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, labor 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 Fig. 4(b)). The unemployment insurance replacement rate is set to $\omega_u = 0.5$ following (Krueger et al., 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 et al. (2007).

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.[25] 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.[26] Table 3 Panel

[25] 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.

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

Table 3
Internally calibrated model parameters and target moments.
Source: Authors' calculations using CEX, CPS, SCF.

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≤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.

A and Fig. 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. 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 Fig. 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 Fig. 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.[27] 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.

4.3. Model fit

Fig. 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 good 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.

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. While all of the shocks are transitory, we assume that the stay-at-home shock and mortgage interest rate shock are somewhat persistent. We explain our assumptions about this persistence below in Section 5.1 and explore the robustness of our results to these assumptions in Section 5.4.

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.[28] 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.[29] The unemployment shocks include a rise in the job separation rate for all age groups and a fall in the job

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

[28] 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.

[29] Fang et al. (2020) and Graham and Ozbilgin (2021) model search and matching models of the labor 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.

Table 4
Parameters and moments calibrated for the pandemic experiment.
Source: Authors' calculations using CEX, FRED.

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.

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 to all households 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.[30] Specifically, we assume that all households in the model receive stimulus payments of $2400 in 2020 and $4000 in 2021.[31] We assume unemployed households receive extra benefits of $12,000 in 2020 and $10,800 in 2021.[32]

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.

5.2. Aggregate responses to the pandemic shocks

Fig. 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 Eq. (2). House prices in the model rise by a little over 7 percent, consistent with observed excess house price growth in 2020 (see Table 4). Rental prices rise by significantly more than is observed in the data.[33] We discuss alternative assumptions about the rental market and rental rates in Section 5.4.

Panel (f) shows a small increase in the homeownership rate from 68 percent in 2019 to 70 percent by 2022. The homeownership rate slowly returns to its steady state value as the shocks dissipate. The higher ownership rate reflects the aggregate increase in housing demand in response to the preference shocks, lower mortgage rates, and stimulus measures. This increase in housing demand translates into higher house prices because housing supply is assumed fixed along the transition path.

Panel (i) shows that household net worth increases by over 10 percent in 2020 and remains elevated for several years. The rise in net worth in the model mostly reflects the rise in house prices, consistent with Financial Accounts data, which show that the increase in household wealth during the pandemic was largely driven by asset revaluations (Batty et al., 2021).

Finally, panels (g) and (h) show that consumption of at-home goods rises while consumption of away-from-home goods falls, in line with the significant shift in observed consumption expenditures documented in Fig. 2. This change in the allocation of consumption expenditures is a direct result of the change in preferences associated with the stay-at-home shock.

Fig. 6 illustrates a decomposition of 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 increase in house prices, while the fall in mortgage rates accounts for

[30] 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.

[31] We assume households in the model consist of two adults, so we give them two checks for each round of stimulus. The payment of $4000 in 2021 reflects the $600 checks paid out in late December 2020 and the $1400 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.

[32] Federal Pandemic Unemployment Compensation, created under the CARES Act, provided an additional $600 per 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 per week from August to September 2020 (6 weeks) for a total of $1200. The American Rescue Plan Act gave UI recipients an additional $300 per week from late December 2020 to September 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 et al. (2021) and Ganong et al. (2021).

[33] According to data from FRED, the annual growth rate of the CPI component 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).

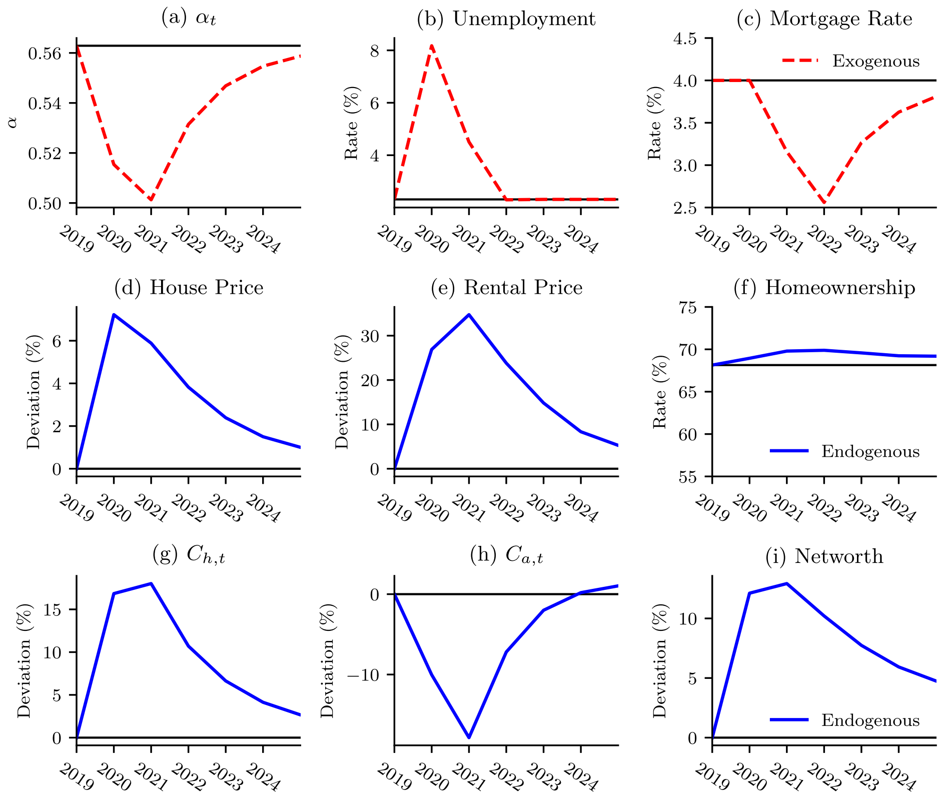

Fig. 5. Impulse responses for pandemic experiment shocks.

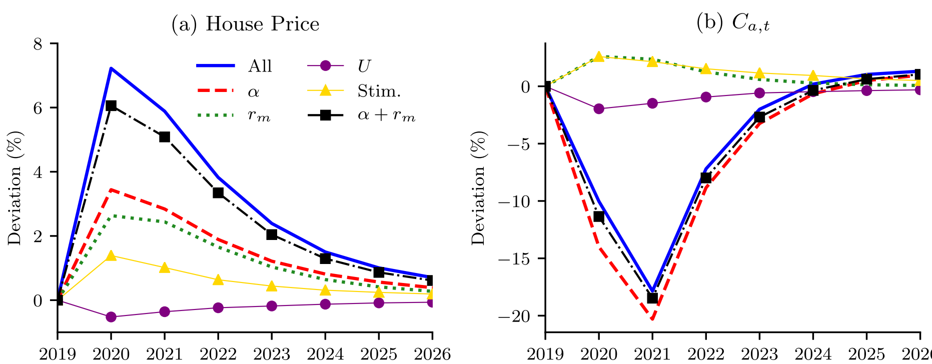

Fig. 6. Impulse responses to separate pandemic shocks.

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.[34]

Our model suggests that lower mortgage rates do not materially amplify the response of house prices to the stay-at-home shock. Fig. 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. 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 the stay-at-home shock increases housing demand. To understand why the interaction between lower mortgage rates and the stay-at-home shock does not have a quantitatively large effect 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 whose value of purchasing a house is very close to the value of renting:

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

[34] As Graves (2020) shows, the presence of unemployment insurance significantly dampens the aggregate demand effects of business cycle shocks in heterogeneous agent models.

Table 5
Fraction of PTI dominant marginal house buyers.

	Steady state	Pandemic shocks			
		Preferences	Preferences and mortgage rate	Mortgage rate	All shocks
Fraction PTI-dominant (%)	7.02	9.15	3.02	3.05	0.93

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).

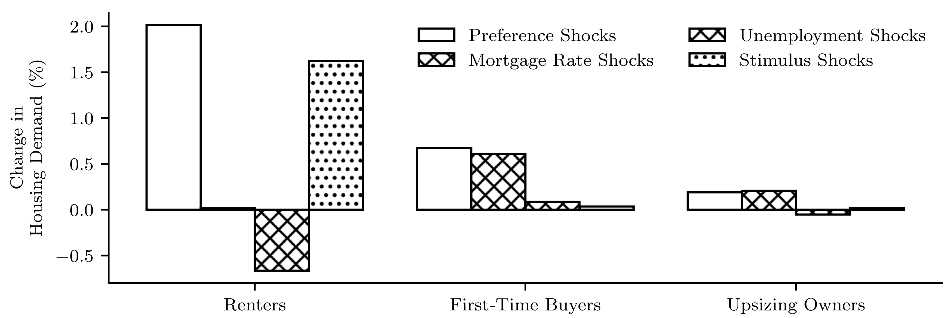

Fig. 7. Changes in house size by housing tenure, partial equilibrium.

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 of a direct increase housing demand and looser borrowing constraints due to lower mortgage rates.[35]

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. Fig. 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 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

[35] This lack of amplification is consistent with the model in Kaplan et al. (2020a), where a relaxation of borrowing constraints does not amplify the house price response to an increase in expected future housing demand.

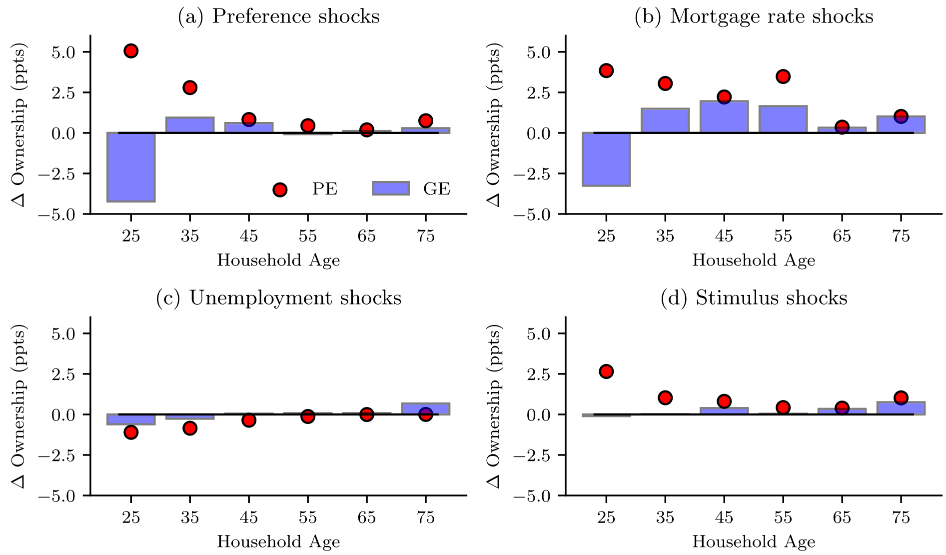

Fig. 8. Homeownership changes in partial equilibrium and general equilibrium. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

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. Fig. 8 shows changes in homeownership rates by age relative to steady state. We show the effects of each of the four shocks in general equilibrium (blue bars) and in partial equilibrium (red dots). The differences between partial equilibrium and general equilibrium effects of the pandemic illustrate 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 the homeownership rate of households aged 25–35 declines. This crowding out of young households in general equilibrium is to the benefit of households aged 35–55, who enjoy a moderate increase in homeownership.

Panel (b) of Fig. 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 (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.

Figures C.1 and C.2 in Online Appendix C.3 reinforce the results of Fig. 8. They illustrate the general equilibrium changes in house size choices of renters and owners in response to the pandemic shocks. Among homeowners in the first two years of the pandemic, there is a spike in demand for the largest house sizes and a fall in demand for smaller house sizes. For renters, there is a significant fall in demand for the largest rental units, and a compensating increase in demand for smaller rental units. These results reflect the fact that general equilibrium increases in house prices tend to squeeze housing demand of younger and poorer households. It is the older and wealthier households, who tend to buy larger and more expensive houses, that remain active in the housing market when house prices rise during the pandemic.

5.4. Robustness

We now explore the sensitivity of our model results to important assumptions about the structure of the rental market and the persistence of pandemic shocks.

First we consider the importance of our assumptions about the rental market. As shown in panel (e) of Fig. 5, the aggregate rental price in the model is extremely sensitive to the pandemic shocks. This is both inconsistent with observed aggregate rental prices, but also with the small estimated response of rental rates in the empirical exercise of Section 2.3.[36] In the baseline model, the response of rents is entirely due to the user-cost Eq. (2). In our experiments, house prices rise on impact and then fall back to steady state as the pandemic shocks dissipate. Higher rents then compensate the rental firm for the present discounted value of capital losses along the transition path.

In Online Appendix C.3 we explore the effect of alternative assumptions about the structure of the rental market. We first consider a model in which housing and rental markets are segmented and supplies of owner-occupied and rental housing are fixed along the transition path. In this version of the model, house prices adjust to clear the housing market and rental prices adjust to clear the rental market, independently of the user cost equation. Second, we consider a model in which rents are exogenously held fixed reflecting the possibility of long-term or sticky rental price contracts.[37] In this version of the model, the supply of rental housing is perfectly elastic at the steady state rental rate and house prices adjust to ensure that total housing

[36] See Table B.9 in Online Appendix B.

[37] For empirical evidence on the existence of sticky rental prices, see Genesove (2003), Suzuki et al. (2021) and Aysoy et al. (2014). For a theoretical treatment, see Gallin and Verbrugge (2019).

demand (i.e. the sum of owner and renter demand) equals total housing supply. We solve these models using the same sequence of shocks as in the baseline analysis, but under the different assumptions about rental market structure. Figure C.3 reports the results. Under the assumption of segmented markets, rental prices rise by much less than in the baseline model and the homeownership rate is nearly constant. Under the assumption of exogenously fixed rental prices, rents are constant but the homeownership rate declines by 4 percentage points. Under both assumptions, equilibrium house prices and consumption patterns are essentially the same as they are in the baseline model. The main conclusion is that alternative assumptions about the structure of the rental market do not affect our conclusions about the aggregate increase in housing demand, but they do affect the allocation of housing demand across rental and owner-occupied properties.

Second, we consider the importance of our assumptions about the persistence of pandemic shocks. As discussed in Section 5.1, we calibrate the persistence ρ_{α,r_m} of both the preference and mortgage interest rate shocks to target the overall increase in house prices observed in 2020. In Figure C.4 in Online Appendix C.3 we re-run our pandemic exercise under each of the following three assumptions: no persistence in preference shocks, no persistence in interest rate shocks, and no persistence in either preference or interest rate shocks. We use the same size of the shocks in 2020 and 2021 as in the baseline experiment (see Table 4), but adjust the persistence of preference and interest rate shocks in turn. Panel (a) of Figure C.4 shows that absent persistence in the shocks, house prices in 2020 and 2021 would be significantly lower. Removing persistence from only the preference shocks or the interest rate shocks reduces peak house prices from 7.2 percent above steady state in the baseline model to around 6 percent above steady state. Removing persistence from both shocks reduces peak house prices to around 5 percent above steady state. Thus, persistence in the shocks accounts for up to 30 percent of the overall increase in house prices during the pandemic period.

6. Conclusion

The pandemic forced households to spend more time and money at home, which appears to have had 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 we show 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, to maintain computational tractability we combine households' liquid savings and mortgage debt into a single net asset position. This implies that our model is not able to match the large rise in personal savings during the pandemic. Some have suggested that the rise in household savings may have contributed to housing demand (see, for example, Bowman, 2021), possibly because it enabled households to make mortgage downpayments more easily than prior to the pandemic. We expect any additional boost to house price growth from this channel to be small compared to the effects of the shocks we model, especially since we account for the rise in household income from fiscal stimulus. However, future work could explore the "excess savings" channel by considering a model that separates liquid savings and mortgages, and directly restricts consumption opportunities early in the pandemic along the lines of Carroll et al. (2020). Finally, we do not explicitly model the effects of working from home. While changing consumption patterns are one way to rationalize an increase in 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.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jhe.2022.101908.

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