# Fiscal Stimulus Payments, Housing Demand, and House Price Inflation

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**Abstract**

During the COVID-19 pandemic, the U.S. housing market experienced an unprecedented boom, with house prices climbing at record rates despite widespread economic disruptions. This paper studies whether the fiscal stimulus transfers—specifically the Economic Impact Payments (EIPs) and expanded Child Tax Credit (CTC) payments totaling over $900 billion—contributed to the surge in housing demand and house prices. These payments were substantial relative to household savings and typical down payments, potentially alleviating liquidity constraints for marginal homebuyers. The analysis shows that lower-income households, who benefited from a significant increase in disposable income due to stimulus payments, experienced greater increases in homeownership rates and housing consumption. A regression kink design exploiting income-based eligibility thresholds suggests a causal relationship between stimulus payments and housing outcomes. Examining variation across regions, I find a strong positive correlation between average stimulus payments and house price growth from 2019 to 2021. This relationship cannot be explained by changes in non-transfer income, population size and density, population growth or migration, exposure to remote work, pre-2020 per capita income or house price levels, or differential housing trends. It holds both across MSAs within the same states and across counties within the same MSAs. The findings suggest that the pandemic stimulus programs contributed to the recent surge in house prices and inflation and highlight an important housing channel in the transmission of fiscal transfer payments.

**Keywords:** Stimulus payments, fiscal policies, housing demand, house prices, homeownership, inflation

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# 1 Introduction

The U.S. housing market experienced a sharp boom during the COVID-19 crisis of 2020 and 2021. The house prices climbed at a record pace, reaching peak annual growth rates of nearly 20% in the second half of 2021 (Figure 1). The pace of house price growth represents a sharp break from pre-pandemic levels and eclipses the growth rates during the housing boom leading up to the 2008 financial crisis. This recent boom was unusual and surprising to many because it happened at a time when the pandemic wreaked havoc on people's lives, employment, income, and economic activities.

What explains the strong housing demand during this period? One possible explanation is that despite the damages that COVID-19 had on the economy, U.S. household finances remained healthy during the pandemic. Indeed, the household sector had strong balance sheets entering into the crisis, and crucially, the government provided unprecedented support for households through various stimulus and relief programs. These fiscal transfers led to an increase in household income despite the job and income losses from shutdowns and other COVID-19 related shocks. The rise in household income and liquidity contributed to an increase in household spending and savings, with some suggesting that the fiscal transfers played an important role in driving the recent surge in inflation.

In this paper, I study whether the fiscal stimulus transfers provided during the pandemic helped fuel the demand for housing and the sharp appreciation of house prices. The investigation is useful for understanding the drivers of the recent housing boom and, more broadly, the impact of fiscal transfer payments on consumer expenditure and the overall economy. This is particularly relevant as stimulus payments have become an increasingly important policy instrument for economic stabilization. Notably, housing consumption has been largely omitted in the large body of research examining the impact of transfer payments on consumer spending. While recent research emphasizes the importance of spending on durable goods as payment size increases, there remains disagreements about whether these payments can meaningfully impact housing transactions (e.g., Beraja and Zorzi, 2023; Berger et al., 2023; Laibson et al., 2023).

The paper examines the impact of the over $900 billion economic impact payments (EIPs) and expanded child tax credit (CTC) payments,[1] which provided historic transfers

[1]EIPs, at a total of over $800 billion, represent the lion's share of transfer payments examined in the paper. For simplicity, in what follows, I will use the term "stimulus payments" or "payments" to refer to the total EIPs and child tax credit payments.

of income from the federal government to households. The three rounds of EIPs alone amount to $11,400 for a family of four eligible for the full payments. In addition, the expanded CTCs made fully refundable by the 2021 American Rescue Plan provided an additional $6,000-$7,200, with half disbursed in advance during 2021. As discussed in the paper, these amounts are substantial relative to the median household savings and the typical down payments of recent home buyers, and could raise housing demand by easing household budget and borrowing constraints. A 2021 Redfin survey found that stimulus money is the second-most common way of accumulating money for a down payment among prospective first-time home buyers, after savings directly from paychecks.[2] From a borrowing constraint perspective, large transfer payments effectively relax down payment constraints, which existing quantitative housing models have shown to have a substantial positive effect on house prices (e.g., Favilukis et al., 2017; Greenwald and Guren, 2024; Gupta et al., 2023). In addition, mortgage interest rates declined during this period, which, as shown by Greenwald and Guren (2024), can significantly amplify the effects of relaxing credit constraints.

To set the stage for the empirical analyses, I start by summarizing the changes in household income across the income distribution using data from Blanchet et al. (2022). The data highlight the substantial role of government transfer payments in stabilizing and boosting the incomes of lower-income households. Specifically, from 2019 to 2020 and 2021, regular income changed by -7.7% for the bottom 50%, -2.2% for the middle 40%, and 0.3% for the top 10%. After accounting for transfer payments, these changes shift dramatically to increases of 32%, 18.8%, and 1.3%, respectively.

Motivated by these patterns, I examine changes in housing consumption across different income groups. I find that lower-income households experienced increases in both homeownership and housing consumption—measured by rooms per person—during 2020–2021 relative to higher-income households. The effects become more pronounced as household income declines, consistent with the relatively larger proportional boost from stimulus payments to lower-income groups. The findings suggest that stimulus payments helped facilitate transitions into homeownership for first-time buyers and enabled existing homeowners to upgrade their living conditions.

To more directly identify the effects of stimulus payments, I leverage the phased reduction in payments for incomes above certain limits and implement a regression kink design.

[2] See https://www.redfin.com/news/homebuyer-survey-stimulus-down-payment/.

Using the 2021 American Community Survey (ACS) microdata, I find a significant decline in the slope of the income-housing outcomes relationship just above the eligibility cutoff. This pattern is not observed before the pandemic or around placebo thresholds in 2021. These findings are consistent with a causal effect of stimulus payments on housing consumption and homeownership rates. The estimates suggest that households with incomes exceeding the limit by $10,000 (resulting in a reduced payment of $1,600 compared to the full $6,400 for a childless couple) exhibit a 0.8-1.9 percentage point decline in homeownership and a 0.03–0.05 decline in rooms per person, relative to those at the income cap.

To further assess how stimulus payments affected housing demand, I examine changes in loan-to-income (LTI) ratios across income groups. From 2019 to 2021, lower-income borrowers saw a significantly larger increase in LTI ratios compared to higher-income borrowers. This pattern suggests that stimulus payments helped ease down payment constraints, allowing liquidity-constrained households to access larger mortgages relative to their income.

I then turn to regional variation and examine the relationship between stimulus payments and housing outcomes across metropolitan statistical areas (MSAs). I find a strong positive correlation between the average amount of stimulus payments and house price growth during 2020–2021. This positive relationship persists when controlling for changes in other transfer payments and non-transfer income, changes in unemployment rate, population size and density, population growth and migration, and exposure to the shift to remote work.

Quantitatively, estimates indicate that a 10 percentage-point increase in the share of population eligible for the full $3,200 payments is associated with a 1–2% increase in house prices from 2019 to 2021. Equivalently, given an average household size of 2.5, a 10-percentage-point increase in the share of households eligible for $8,000 payments corresponds to a 1–2% increase in house prices.

To further address concerns about confounding factors, I conduct several additional analyses. First, controlling for pre-pandemic per-capita income yields similar results: cities with a higher share of stimulus-eligible residents experienced faster house price appreciation, even when comparing cities with similar income levels. Second, the results are not driven by pre-existing differences in house price levels or trends. Third, the positive relation between house price growth and stimulus payments holds across MSAs within the same states, suggesting that state-level shocks or policies do not explain the findings.

Importantly, the observed house price growth does not appear to be driven by shifts in housing supply. Both housing transaction volumes and home listings increased significantly more in high-payment areas during this period, consistent with demand-driven price increases. Moreover, the rise in transactions was not fueled by easier credit conditions—if anything, mortgage denial rates rose slightly in these areas, indicating tighter credit supply.

While most of the analysis focuses on variation across MSAs, I also conduct within-MSA analyses to further address concerns about unobserved local shocks. Specifically, I compare stimulus payments and house price growth across counties within the same MSAs. Controlling for factors known to influence within-city migration during the pandemic—such as population density and distance to the central business district (Gupta et al., 2022; Ramani and Bloom, 2022)—I find a similar positive relationship between stimulus payments and house price growth at the county level.

Lastly, extending the analysis beyond 2021, I find that house prices in high-payment areas continued to strengthen into early 2022 and remained elevated through 2022 and much of 2023. By 2024, however, these areas began to experience relative price declines compared to low-payment areas. These findings align with the idea that the stimulus payments pulled forward housing demand, leading to price acceleration lasting a few years, followed by a correction.

Taken together, these findings indicate that stimulus payments had a substantial impact on household housing demand and contributed meaningfully to house price growth during the pandemic. Extrapolation from the cross-sectional estimates suggests that fiscal transfers were a key driver of the pandemic-era housing boom. The findings underscore that housing consumption and investment could be an important channel through which the fiscal transfer payments affect the real economy. Moreover, since shelter costs are a major component of the Consumer Price Index (CPI), the evidence also implies that stimulus payments contributed to the recent surge in inflation.

A number of studies examine the household spending response to the pandemic stimulus payments, with a focus on the initial impacts of payments in 2020 (Cox et al., 2020; Coibion et al., 2020; Parker et al., 2022; Chetty et al., 2023; Baker et al., 2023). These studies generally find that there was a consumption response to the stimulus payments and that the response was negatively related to household income and liquidity. Prior studies have also examined consumer spending responses to previous fiscal stimulus payment programs such as the tax rebate of 2001 and the stimulus payments of 2008 (e.g., Shapiro and Slemrod, 2003; Johnson et al., 2006; Agarwal et al., 2007; Parker et al., 2013). Housing demand and housing transaction activities have generally been omitted in this literature. Recent quantitative models of fiscal stimulus highlight the significance of durable goods purchases (e.g., Beraja and Zorzi, 2023; Berger et al., 2023). While Beraja and Zorzi (2023) conjecture that stimulus checks are likely too small to matter for home purchases, Berger et al. (2023)'s model predicts that even relatively small cash transfers can have a sizable impact on the demand for owner-occupied housing due to the financial constraints faced by marginal buyers. Also related, Hsu et al. (2018) find that unemployment insurance mitigated foreclosures and supported home values from labor market shocks during the Great Recession.

Existing studies of the housing market during the pandemic generally focus on the effect of remote work and population migration (e.g., Mondragon and Wieland, 2022; Gupta et al., 2022; Stanton and Tiwari, 2021; Brueckner et al., 2021; Gamber et al., 2022; Howard et al., 2023). There has been very limited empirical evidence on other possible explanations of the housing boom. Griffin et al. (2023) find that areas with greater paycheck protection program (PPP) loan fraud experienced faster growth in house prices. Diamond et al. (2023) argue that the post-Covid inflation driven by fiscal and monetary stimulus boosted housing demand by inflating away existing mortgage debt of constrained homeowners. There is a large literature studying the housing boom prior to the 2008 financial crisis, with a focus on the roles played by cheap credit and shifts in expectations. More broadly, the paper fits into the literature studying the impact of income and credit constraints on housing demand and house prices. Section 2.2 discusses some of these studies.

The paper is also related to the literature examining the impacts of other government pandemic relief programs such as the PPP (e.g., Granja et al., 2022; Bartik et al., 2020; Autor et al., 2022), unemployment insurance (e.g., Ganong et al., 2020; Larrimore et al., 2022; Ganong et al., 2024), and the assistance for state and local governments (e.g., Clemens et al., 2022). These studies generally focus on evaluating the costs and effectiveness of these programs. Some of these programs, especially PPP and the unemployment insurance that are comparable in size to the EIPs, also bolstered household finances during the pandemic, and thus were likely to have supported the housing demand during this period. The payments made through these programs were directly tied to an area's exposure to COVID-19 and related restrictions, and as a result it is more difficult to identify their effects using variation across areas. This paper's analyses control for these other transfers when focusing on the effects of stimulus payments.

# 2 Stimulus payments and housing demand

This section provides more details on the three rounds of EIPs and the expanded CTC. It then discusses the potential channels through which the payments could impact housing demand and some related literature.

## 2.1 Stimulus payments

Since the onset of the COVID-19 pandemic in early 2020, the federal government provided unprecedented support for families, businesses, and local governments.[3] At a total cost of more than $5 trillion, the fiscal policy response is about four times as large as the 2009 American Recovery and Reinvestment Act passed to help the U.S. economy recover from the global financial crisis (Romer, 2021). This paper focuses on the three rounds of direct payments to individuals totaling over $800 billion, known as the economic impact payments, as well as the over $100 billion expanded child tax credits. These payments provided significant income and liquidity support for individuals irrespective of whether they suffered from income losses during the pandemic.

The first round of stimulus checks, authorized by the Coronavirus Aid, Relief, and Economic Security Act (CARES Act) in March 2020, provided EIPs of up to $1,200 per eligible adult and $500 per qualifying child under age 17. The payments were reduced for individuals with adjusted gross income (AGI) greater than $75,000 ($150,000 for married couples filing a joint return), with childless households with incomes up to $99,000 (or $198,000 if married and filing jointly) still eligible for payments. In total, these stimulus checks amounted to more than $270 billion.[4]

[3] See the summary of these economic relief programs by the Department of the Treasury https://home.treasury.gov/policy-issues/coronavirus.

[4] See IRS SOI Tax Stats – Coronavirus Aid, Relief, and Economic Security Act Statistics.

The COVID-19-related Tax Relief Act of 2020, enacted in late December 2020, authorized additional payments of up to $600 per adult and per qualifying child under age 17. The AGI thresholds at which the payments began to be reduced were the same as the earlier round, with the payments phasing out entirely for households with incomes above $87,000 for single filers or $174,000 for married couples without children. These payments totaled over $140 billion.

The American Rescue Plan Act of 2021, enacted in early March 2021, provided EIPs of up to $1,400 for eligible individuals or $2,800 for married couples filing jointly, plus $1,400 for each qualifying dependent, including adult dependents. The eligibility for the full amount was the same as prior rounds, but the phase-out occurred more quickly, with households with incomes above $80,000 for single filers or $160,000 for married couples receiving no payments. This third round of EIPs cost over $400 billion, nearly the combined amount of the first two rounds.

The American Rescue Plan Act also increased the child tax credit from $2,000 to $3,000 per child for children aged 6 to 17 and to $3,600 for children under 6. The Act also made the CTC fully refundable, allowing all eligible families to receive the full credit benefit. The Act mandated the Department of the Treasury to establish a program for making periodic advance payments of the CTC, with a total amount equal to 50% of the CTC for the 2021 tax year. In total, around $94 billion were disbursed in 2021 in the form of advance payments.[5]

Altogether, the three rounds of EIPs and the expanded CTC distributed a total of $914 billion or around $2,750 per person.[6] For a family of four with income below the threshold, they would be eligible for $11,400 EIPs plus an additional $6,000–$7,200 CTC, half of which can be received in 2021. This is a significant amount relative to an average family's annual savings out of income or total household savings. For example, according to the 2019 Survey of Consumer Finances, the median household had only $26,000 in non-retirement financial assets including deposits, bonds, and stocks. These stimulus

[5] See IRS SOI Tax Stats – Advance Child Tax Credit Payments in 2021. These advance payments are somewhat smaller than the total cost of the expanded CTC. The Joint Committee on Taxation estimates that the one-year expansion of the CTC would cost about $110 billion.

[6] Figure A1 plots the total EIPs and advance CTC payments received by individuals in different AGI groups: those with AGI below $20,000 (including those with zero or negative AGI and those who did not file a tax return in 2019 or 2020), between $20,000 and $50,000, $50,000 and $75,000, $75,000 and $100,000, $100,000 and $200,000, and over $200,000.

payments, on top of the generous unemployment insurance and other stimulus programs,[7] help more than offset income losses from unemployment or other COVID-19-related shocks in 2020 and 2021. The disposable personal income per capita, according to the BEA, increased from $49,585 in 2019 to $53,038 in 2020 and further to $56,088 in 2021.

## 2.2 Stimulus payments and housing demand

Previous research on the consumption response to stimulus payments reports significant spending on both non-durables (e.g., Johnson et al., 2006) and durables (e.g., Parker et al., 2013). This spending behavior is interpreted as an indication that stimulus payments help ease household liquidity constraints. These studies also suggest that durable purchases could become more responsive as payments become larger because durables are lumpy and can be financed with external funds (Beraja and Zorzi, 2023). Underscoring the important role of borrowing constraints for housing demand, a large number of studies emphasize credit supply shocks driven by shifts in lending standards (down payments, loan-to-income ratio, etc.) as an important contributor to the housing boom prior to the 2008 financial crisis.[8] In a recent study using survey data, Fuster and Zafar (2021) find that people's willingness to pay (for the same house) increases by as much as 15 percent on average when the down payment is reduced from 20 percent to 5 percent.

According to the 2021 American Housing Survey, the median and the 75th percentile household size of home buyers was 2 and 4, respectively. Households of these sizes could be eligible for $6,400 and $11,400 EIPs plus any additional CTCs. The median home purchase price was $266,000 and the typical down payment was around 8%. These figures suggest that the stimulus payments of 2020 and 2021 could significantly relax the credit constraints faced by the marginal home buyers, particularly first time buyers of starter

[7] Federal Pandemic Unemployment Compensation (FPUC) provided a weekly supplement on top of all UI benefits. FPUC provided a $600 weekly supplement between April and July 2020 and was reauthorized at $300 weekly from January 2021 through the beginning of September 2021. FPUC payments from April 2020 through September 6, 2021, totaled $442.3 billion. Ganong et al. (2020) find that between April and July 2020, 76% of workers eligible for regular unemployment compensation have statutory replacement rates above 100%, meaning that they are eligible for benefits that exceed lost wages.

[8] See, among others, Mian and Sufi (2009), Favara and Imbs (2015), Di Maggio and Kermani (2017), Favilukis et al. (2017), Justiniano et al. (2019), Mian and Sufi (2021), Greenwald and Guren (2024), Adelino et al. (2024), and Drechsler et al. (2022). Chodorow-Reich et al. (2022) highlight the role of city-level fundamentals in driving the housing boom-bust-rebound cycle since 2000. Berger et al. (2020) study the effects of the refundable First-Time Homebuyer Credit program of 2009, and find that zip codes with greater exposure to the program experienced greater home sales and house price growth.

homes. Even for existing homeowners, these payments provide a nontrivial amount of additional liquidity, which could lead to self-reinforcing increases in housing demand and house prices (Stein, 1995). Importantly, the rising housing demand by constrained borrowers could cause house prices at all levels to rise in equilibrium (Ortalo-Magné and Rady, 2006; Määttänen and Terviö, 2014; Landvoigt et al., 2015).

While there are few estimates of the effect of transfer payments on house prices, existing studies generally find a large positive effect of LTV constraint relaxation. For example, Greenwald and Guren (2024) estimate that increasing LTV limits from 85% to 99% and PTI limits from 36% to 65% can lead to a nearly 20% increase in house prices with unchanged mortgage rates, and around a 40% increase with an additional two-percentage-point reduction in mortgage rates. In Gupta et al. (2023)'s calibration, an increase in FHA loan cap by $75,000 from $380,000 can raise house prices by up to 20%. By comparison, with an 8% typical down payment, a $10,000 stimulus payment would enable constrained households to take on an additional $125,000 loan. Thus, if down payment constrains are as influential as suggested in the literature, one could reasonably anticipate a substantial effect of the COVID stimulus payments on house prices.

Another distinctive feature of housing is that it represents a combination of a consumption good and an investment asset. As a result, housing can serve as an important savings vehicle for households (Kaplan and Violante, 2014), and expectation of future prices plays an important role in driving housing demand. Shifts in expectations can also have strong interactions with the income and credit effect. For example, an initial impact of income shocks on housing demand and house prices can be amplified by buyers' adaptive expectations (Glaeser et al., 2008). Glaeser et al. (2012), Adelino et al. (2016), Kaplan et al. (2020), and Albanesi et al. (2022), among others, argue that shifts in expectation were an important driver of the 2000s housing boom.

# 3 Data and summary statistics

## 3.1 Measuring stimulus payments of 2020-2021 at the MSA level

The unit of observations in the regional analyses is the Metropolitan Statistical Area (MSA). Personal income data by MSA are from the BEA's Regional Economics Accounts, which report income data by type (wage, investment income, government transfers, etc.)

and geographic location (state, metro, county, etc.). The EIPs are included in both item "Other transfer receipts of individuals from governments", and Addendum item "Refundable tax credits". In addition to the EIPs, the refundable tax credits include the advance child tax credit payments authorized in the American Rescue Plan, as well as various other tax credits that were in effect in 2020 and 2021.[9] While there may have been changes in other tax credits concurrent with the stimulus payments, the magnitude of these changes is negligible relative to the stimulus payments. For example, the American Rescue Plan expanded the health insurance premium tax credit in 2021, but the total increase in spending for this program was approximately \$8 billion–merely about 1% of the total EIPs.

Figure A2 plots the average amount of per-capita refundable tax credits (RTCs) across MSAs since 2010. The amount increases gradually in the years leading up to 2020, reaching \$483 per person in 2019. It then jumped to \$1,332 in 2020 and further to \$2,600 in 2021. Comparing to the amount in 2019, the total increase in 2020 and 2021 stands just below \$3,000. This increase aligns closely with the total EIPs and CTCs per person, suggesting that the changes in these figures since 2019 serve as a good proxy for the amount of stimulus payments received by residents in an MSA. Consequently, the subsequent analysis measures the total per-capita stimulus payments at the MSA level in 2020 and 2021 by the total increases of per-capita RTCs in the BEA data from 2019,[10]

$$Stimulus\ \ payments = RTCs_{2020} + RTCs_{2021} - 2\times RTCs_{2019}. \tag{1}$$

Table 1 reports the summary statistics of stimulus payments as measured in Eq. (1) and other key variables used in the MSA level analyses. The per-capita stimulus payments have an average of \$2,965, ranging from \$2,024 to \$4,188 across MSAs. Figure A3 shows a heatmap of per-capita stimulus payments across MSAs in the sample. Towards the lower end of the spectrum, MSAs such as Boulder, CO, Ithaca, NY, and San Jose, CA have

[9]According to the BEA, the other refundable tax credits include the Health Coverage Tax Credit (2003-2021), Health Insurance Premium Assistance Tax Credit (2014-2021), and the Alternative Minimum Tax Credit (2008-2021).

[10]This simple approach to estimate stimulus payments does not account for the potential MSA-specific growth trend in other RTCs. To address this possibility, an alternative approach is to assume that these items have grown at the same rate in 2020 and 2021 as they did before 2020. The main results are robust to this alternative approach. For example, untabulated results show that the point estimates are generally slightly larger if the growth rate of RTCs from 2018 to 2019 is used to infer the amount of refundable tax credits excluding stimulus payments in 2020 and 2021.

per-capita payments close to \$2,000. At the upper end, El Centro, CA, Laredo, TX, and Yuma, AZ received per-capita payments of around \$4,000.[11]

As discussed in Section 2, because only households with income below certain thresholds are eligible for the stimulus payments, per-capita payments should be negatively related to an MSA's income level. Panel (a) of Figure 2 presents a scatter plot of per-capita payments against the 2019 per-capita income. It shows a strong negative relation between the two with a correlation of -0.52. In the meantime, the figure also shows that there is substantial variation in the amount of stimulus payments among MSAs with similar per-capita income levels. The R-squared from regressing stimulus payments on 2019 per-capita income is 0.27.

The relatively low explanatory power of per-capita income for the per-capita stimulus payment amount might not be surprising given that the per-capita income could be skewed by the top or bottom earners in an MSA, while the amount of stimulus payments depends on the fraction of population below the income thresholds. I next turn to the taxable income data from the IRS to obtain more granular distribution of income at the MSA level. The IRS data report the number of tax returns by income groups and filing status. Panel (b) shows the scatter plot of per-capita payments against the fraction of tax returns with adjusted gross income under \$100,000 in 2019.[12] It shows a positive and very tight relation between the two. The correlation is 0.79 and the R-squared from regressing stimulus payments on the fraction of tax returns below \$100,000 is 0.62.

## 3.2 House prices and other housing data

The Fannie Mae Home Price Index (FNM-HPI) from 1985 to 2022 Q3 is used to plot the quarterly house price growth in Figure 1. The index is a national, repeat-transaction home price index measuring the average price change for all single-family properties in the United States, excluding condos. House price data at the MSA level are obtained from

[11] All three cities have a large Hispanic population. This is not a mere coincidence. Minorities have lower income on average and are more likely to have received the stimulus payments. Figure A4 shows that per-capita stimulus payments are larger in MSAs with a larger share of Black or Hispanic population. Table A1 shows that regressing the amount of stimulus payments (in thousands) on the share of Black and Hispanic population in 2019 at the MSA level produces point estimates of around 0.6 for both variables. This suggests that, on average, Black and Hispanic individuals received approximately \$600 more in stimulus payments compared to White individuals and those from other minority groups.

[12] For married couples filing joint returns, the AGI threshold is \$150,000 for receiving the full payments. The IRS data do not break down returns at \$150,000.

Freddie Mac House Price Index (FMHPI). The indices are constructed using a repeat transactions methodology based on loans that have been purchased by Freddie Mac or Fannie Mae, which are conforming loans below the limits as determined by the Federal Housing Finance Agency (FHFA).

Table 1 reports that on average house prices grew by 31% during the two year period from December 2019 to December 2021. There is also large variation in the degree of house price inflation across MSAs. House prices in MSAs such as Midland and Odessa, Texas barely moved, while in MSAs such as Boise City, Idaho and St. George, Utah they appreciated by well over 50% during this period. Figure A5 shows a heatmap of house price growth of all MSAs in the sample. Unlike the housing boom prior to the 2008 financial crisis, which concentrated in coastal areas and other "sand states" such as Nevada and Arizona, the recent boom has spread more evenly across the country, with MSAs in many inland states such as Idaho, Utah, Tennessee witnessing sharp house price appreciation.

Annual housing permit data by MSA in 2020 and 2021 are from the Census Building Permits Survey. Total housing units by county as of 2019 are from the Census Annual Estimates of Housing Units. The county level data are aggregated to the MSA level using the CBSA-county crosswalk file from the Census. Growth in housing units from 2019 to 2021 is proxied by the total housing permits issued in 2020 and 2021, divided by the total number of housing units as of 2019. Median value of owner-occupied housing units data in 2019 are from the Census American Community Survey (ACS) 1-year estimates. Homeownership data are also from the ACS.

On average, the total number of housing permits in 2020 and 2021 relative to the 2019 housing stock is 2.4%. While this number seems modest, it is substantially larger than the growth rates of housing units in previous years. For example, MSA level housing units on average grew by 1% from 2017 to 2019 and by 0.9% from 2015 to 2017. Housing units growth ranges from around 0 in MSAs such as Danville, IL and Morgantown, WV to over 10% in MSAs such as Austin, TX, Provo-Orem, UT, and The Villages, FL. House prices grew by 53%, 48%, and 32% in these three cities with the highest housing unit growth. Across all MSAs, housing unit growth and price growth are strongly positively correlated with a correlation of 0.49, suggesting a dominant role of increased housing demand in pushing up house prices. In Section 5.3, house price and housing unit growth are combined to create a simple measure of housing demand.

Home listing and inventory data are from Realtor.com. I calculate the percentage change in the number of new listings in 2020 and 2021 from 2019. On average, the number of new listings declines by 7% across MSAs during the two year window. Across MSAs, changes in new listings and house prices exhibit little correlation, with a correlation coefficient of -0.018.

### 3.3 Other data

Population, total income, and transfer income data at the MSA level are all from the BEA. Total transfer income is reported in "Personal current transfer receipts". Unemployment data at the MSA level are from Bureau of Labor Statistics (BLS)'s Local Area Unemployment Statistics (LAUS) program (the smoothed seasonally adjusted metropolitan area estimates).

Table 1 reports the summary statistics of changes in per-capita transfer income excluding stimulus payments (defined as total transfer income minus refundable tax credits) and changes in per-capita non-transfer income (defined as total income minus total transfer income) from 2019 to 2020 and 2021. On average, transfer income excluding stimulus payments increased by around \$4,500 per person in 2020 and 2021, to a large extent driven by increases in unemployment insurance during the pandemic. Across MSAs, changes in per-capita transfers excluding stimulus payments have a correlation with changes in unemployment rates from 2019 to 2021 of 0.32. In contrast, the correlation between per-capita stimulus payments and changes in unemployment rates from 2019 to 2021 is -0.23.[13]

Non-transfer income increased by around \$3,000 per person, most of which occurred in 2021. The MSA that had the largest decline in non-transfer income happens to be the oil-rich Midland, Texas that experienced the lowest house price growth. Its residents saw a decline in income by \$56,000 per person from 2019 to 2021.[14] This single data point illustrates the importance of controlling for changes in local income levels unrelated to stimulus payments.

I obtain the population migration data from the IRS, which are based on year-to-year address changes reported on individual income tax returns filed with the IRS. I aggregate

[13] Unemployment rate rose sharply early in the pandemic and recovered quickly during the second half of 2020 and 2021. Changes in per-capita non-stimulus transfers and stimulus payments in 2020 have a correlation with changes in unemployment rate from 2019 to 2020 of 0.49 and -0.2, respectively.

[14] Despite the decline, Midland's per-capita income still ranked No. 1 in the country in 2020 and No. 2 in 2021.

the total inflow in the county-to-county migration data to the MSA level using the CBSA-county crosswalk file from the Census. MSAs with the largest total in-migration in 2020 and 2021 as a fraction of total population in 2019 are Coeur d'Alene, ID, Greeley, CO, and Lakeland-Winter Haven, FL with an inflow-to-population ratio of over 12%.

Population density data are obtained from the Census (Wilson et al., 2012) and measured as the number of people per square mile. Population-weighted density represents the average density across all census tracts within each area. The most recent available Census data, from 2010, is used in this paper.

Mortgage data are from the Home Mortgage Disclosure Act (HMDA) dataset. HMDA requires financial institutions to report and publicly disclose loan-level information about mortgages. Every year, tens of millions of loans made by thousands of financial institutions are reported and recorded in the database. The data contain a large number of loan-level variables including loan purpose, loan amount, location of property, and borrower demographic information which includes borrower income in recent years. To measure the number of mortgage-financed housing transactions at the MSA level, I aggregate the number of originated home purchase mortgages to the MSA-year level. On average, the number of home purchase mortgages grew by 28% during 2020-2021 from the 2019 level.

# 4 Household-level results

In this section, I use household level data to examine changes in household income, homeownership rate, housing consumption, and debt-to-income ratios across different income groups. In addition, I implement a regression kink design to estimate the effect of stimulus payments on homeownership and housing consumption.

## 4.1 Changes in income by income groups

I first document changes in household income across the income distribution during the pandemic. The goal is to show how incomes would have changed in the absence of government transfer payments and to highlight the income gains driven by those transfers. To this end, I use data from Blanchet et al. (2022), which are well suited for this purpose. They provide various measures of income for households in the bottom 50%, the middle 40%, and the top 10% of the distribution.

Table 2 reports the average annual income per household by income measure and income group from 2019 to 2021. Starting with factor income, which includes income earned from labor and capital before taxes and transfers, the total change in household income in 2020 and 2021 relative to 2019 were -7.7%, -2.2%, and 0.3% for the bottom 50%, the middle 40%, and the top 10%. This finding is consistent with the fact that lower-income households were more likely to hold jobs that cannot be performed remotely and thus suffered from greater income losses during the pandemic.

I next turn to pretax income, which among other things, captures the effects of expanded unemployment insurance during the pandemic. Panel B shows that pretax income rose by 3.1% for the bottom 50%, 1.3% for the middle 40%, and fell by 4.2% for the top 10%. These changes suggest that the expansion of unemployment benefits more than offset income losses for households in the bottom 90% of the income distribution.

Lastly, I examine disposable income, measured by Blanchet et al. (2022) as pretax income minus taxes plus cash and quasi-cash transfers. Panel C shows a striking increase in real income for lower- and middle-income households: disposable income rose by 32% for the bottom 50% and 18.8% for the middle 40%, primarily driven by large transfer payments during the pandemic.

Overall, these statistics suggest that lower-income households experienced worse labor market outcomes during the pandemic. However, the historic government transfer payments provided an enormous boost to their incomes.

## 4.2 Changes in housing consumption by income groups

The previous section shows that the government transfer payments lead to sharp increases in household disposable income during the pandemic, especially among households with lower income. As discussed above, the transfer payments were also substantial relative to household savings and typical down payments and thus can alleviate the financial constraints of marginal home buyers.

To examine how housing consumption changed across the income distribution, I use data from the Integrated Public Use Microdata Sample (IPUMS) of the American Community Survey (ACS) for the years 2019 to 2021 (Ruggles et al., 2023). I begin by analyzing homeownership status. Following Adelino et al. (2018), I sort households into income quintiles based on reported family income in each year and track the changes in homeownership rates before and after 2020.[15] I estimate a regression of homeownership status on income quintile indicators and their interactions with a 2020–2021 indicator variable, controlling for household head age and household size.

Column (1) of Table 3 shows that households in the bottom three quintiles experienced an increase in homeownership rates after 2020 relative to households in the top quintile. In column (2), I include interactions between household size, household head age, and the post-2020 indicator to allow these factors to have differential effects on homeownership during the pandemic. With these additional controls, lower-income households exhibit an even larger relative increase in homeownership. Column (3) further includes county-by-year fixed effects to compare households located in the same county. Compared to the top income quintile, the homeownership rates of households in the bottom four quintiles increase by 2.2, 1.5, 0.8, and 0.4 percentage points, respectively. This more pronounced effect among lower-income households aligns with the fact that the fixed transfer payments provide a relatively larger boost to their income and savings.

Homeownership reflects the margin of adjustment from renting to owning, but it does not capture changes in housing consumption that occur without changes in ownership status. While potentially less binding than for renters, down payment constraints can still be significant for existing homeowners (Stein, 1995). To examine this additional margin of adjustment, I next examine housing consumption. Since the ACS data do not include housing values, I follow the literature and use the number of rooms as a proxy for the quantity of housing consumption (e.g., Flavin and Nakagawa, 2008; Han, 2010).

Column (4) reports the results using the number of rooms as the dependent variable. The estimates show that relatively to households in the top 10%, those in the bottom 90% experienced a significant increase in the number of rooms, with the effect being more pronounced among lower-income households. Column (5) replaces the number of rooms by rooms per person. It shows that, relative to households in the top 10%, households in the bottom quintile and second-lowest quintile increases in rooms per person by 0.054 and 0.025, respectively. These findings suggest that lower-income households were more likely to increase their living space during the pandemic, despite the popular narrative

[15] The upper income limits for the bottom four quintiles in 2019 are $27,000, $50,900, $80,000, and $130,300, respectively. Thus nearly all households in the bottom three quintiles are eligible for the full stimulus payments. According to the IRS data, the majority of tax returns with income between $75,000 and $100,000 or over $100,000 are filed jointly by married couples. Thus the majority of households in the fourth quintile would also be eligible for the payments. Only a small fraction of households in the top quintile with married couples and income below $150,000 would be eligible for the full payments.

that high-income households were the ones relocating from high-density urban areas to lower-density suburbs in search of more space for remote work.

Column (6) and (7) examine homeowners and renters separately. The results indicate that the increase in the number of rooms is largely driven by homeowners, with little effect observed among renters. The lack of increase in housing consumption among renters implies that while some renters have transitioned into homeownership—reflecting a high marginal propensity to spend on housing (MPX)—those who remained renters did not expand their living space and likely had a higher non-housing MPC out of the stimulus payments.

## 4.3 Regression kink test based on income limits

One potentially effective approach to assessing the impact of the stimulus payments is to use the income thresholds that determine payment eligibility. Single filers and married couples filing jointly qualify for the full payments if their income fell below $75,000 and $150,000, respectively, with payment amounts gradually phasing out above these thresholds. This structure enables an examination of whether there is any noticeable change, or "kinks," in the homeownership-income relationship around this threshold. A decline in the slope for incomes above the limit would suggest that stimulus payments have positively influenced homeownership.

However, implementing this test using the ACS micro data poses several challenges. First, the income reported in the ACS does not align perfectly with the AGI used to determine payment eligibility. The discrepancy stems from factors such as retirement contributions and other statutory adjustments such as IRAs and health savings account deductions. As a result, many households with reported income above the thresholds in the ACS may have still qualified for full payments, potentially obscuring any clear kink around the threshold. A second limitation is the ACS's lack of historical income data. For example, a household with a 2021 AGI of $160,000 may have received full payments based on a lower 2019 income.

Acknowledging these data limitations, the subsequent analysis implements a regression kink design to examine the relationship between household income and homeownership status reported in the ACS data. I restrict the sample to single-family households that either consist of a married couple or contain no couple and no children under the age of

19. The relevant income thresholds for these two groups are $150,000 and $75,000, respectively. To approximate calendar year income, the ACS's reported income over the past twelve months is adjusted using the correction factor provided by IPUMS. Additionally, all income figures from 2021 are converted to 2019 dollars using the CPI variable from IPUMS.

The model estimated is

$$Own_i = \alpha + \beta_1(Income_i/c_i) + \beta_2(Income_i/c_i) \times \mathbf{1}\{Income_i \geq c_i\} + \gamma X_i + \epsilon_i, \quad (2)$$

where income is normalized by the income limit discussed above, $Own$ is an indicator variable for owning the housing unit, $\mathbf{1}\{Income_i \geq c_i\}$ is an indicator equal to 1 if income is above the limit and 0 otherwise, and $X$ is a vector of control variables that include family size, age group, and an indicator variable for couples in the household.

Panel A of Table 4 reports the results using the 2021 ACS sample across various bandwidths. In column (1) where households with income within 10% of the threshold are used, the coefficient is $-0.124$, though it is not statistically significant. In column (2), where a 12.5% bandwidth is used, the coefficient becomes significantly more negative and statistically significant at the 1% level. The next two columns show that, as the bandwidth expands to 15% and 17.5% of the thresholds, the coefficients remain negative and significant at either the 5% or 1% level.[16] Figure 3 visually confirms the kink in the income–homeownership relationship at the 17.5% bandwidth: while homeownership rates rise with income below the threshold, the relationship flattens above it. The estimates indicate that compared to households comprising married couples with no kids and an income of $150,000 (eligible for $6,400 payments), those with an income of $160,000 (eligible for $1,600 payments) exhibit a relative decrease in homeownership by 0.8 to 1.9 percentage points.

As a placebo test, I repeat the same analysis using the 2019 ACS data. Appendix Table A2 reports that none of the coefficients in the four estimations is statistically different from zero. Appendix Figure A8 shows that the relationship between household income and homeownership is similar below and above the income limits in 2019. Furthermore, untabulated results show that when alternative hypothetical income thresholds of $30,000

[16]The optimal bandwidth selected using the procedure from Calonico et al. (2014) is 0.118 around the threshold. Using this bandwidth yields a coefficient estimate of -0.246, significant at the 1% level.

above or below the actual limits are used, none of the coefficients across the four different bandwidths is statistically negative with the 2021 ACS sample. These results lend further credibility to the regression kink design.

Lastly, I repeat the analysis using the number of rooms as the outcome variable. The results are reported in Panel B of Table 4. While the magnitude of the estimates varies slightly across bandwidths, the results are generally negative and statistically significant. The estimates indicate that, compared to households comprising married couples with no kids and an income of \$150,000, those with an income of \$160,000 experience a relative decrease in rooms per person of 0.03 to 0.05. These findings suggest that the stimulus payments also had a positive effect on housing consumption. Together, these results are consistent with a causal interpretation in which stimulus payments relax housing-related constraints along both the extensive and intensive margins.

## 4.4 Changes in LTI by income groups

If lower-income households used stimulus payments to increase their down payments, we should observe an increase in their LTI ratios. This is because stimulus payments are not counted as income in mortgage applications. As a result, borrowers who applied these funds toward down payments could qualify for larger loans relative to their reported income, thereby raising their LTI ratios. For example, a household earning \$40,000 annually with \$10,000 in savings could secure a \$100,000 loan with a 10% down payment, resulting in an LTI of 2.5. If the household adds \$5,000 from a stimulus payment to increase its down payment, it could now qualify for a \$150,000 loan—raising its LTI ratio to 3.75.

To test this, I turn to transaction-level data and examine the dynamics of LTI ratios across different income levels. For each year from 2018 to 2021, I sort home buyers into five groups based on the level of income reported in HMDA and calculate the average LTI ratio for each quintile and year.[17] Figure 4 shows that the LTI ratio increases for all quintiles from 2019 to 2021, with the most significant rises occurring among lower-income groups. This contrasts with the fact that the LTI levels did not evolve differentially for borrowers across different income brackets during the housing boom prior to the Great Recession (Adelino et al., 2016).

Table 5 presents the analysis of LTI ratios in 2019 and 2021 based on income levels.

[17] The upper income limits for the bottom four quintiles in 2019 are \$52,000, \$73,000, \$100,000, and \$150,000, respectively.

Column (1) shows that relative to borrowers in the top income quintile, borrowers in the bottom two quintiles saw a 0.26 increase in their LTI ratio from 2019 to 2021. In column (2), the estimation allows the change in LTI ratios to vary by borrower age group and the number of applicants. Column (3) further controls for county-by-year effects and shows more pronounced differential changes in LTI ratios across income levels when comparing transactions within the same county. The greater increase in LTI ratios among lower-income borrowers—who were more likely to receive the payments and for whom the payment amounts were more significant relative to their income and savings—is consistent with the view that stimulus payments helped ease down payment constraints.

# 5 MSA-level results

The previous section showed that lower-income households significantly increased their housing consumption during the pandemic, with stimulus payments likely playing a key role in driving this demand. This section turns to housing market outcomes at the MSA level to examine how these changes in demand affected equilibrium prices. The main focus is on house price appreciation across MSAs as a function of stimulus payments received by local residents, controlling for a wide range of other potential housing demand shocks.

## 5.1 Stimulus payments and house prices

The baseline model is a cross-sectional regression of house price growth on stimulus payments and control variables at the MSA level:

$$\Delta HP_i = \alpha + \beta Stimulus\ payments_i + \gamma X_i + \epsilon_i, \tag{3}$$

where $\Delta HP_i$ is the growth of house price in MSA $i$ from 2019 to 2021. $Stimulus\ payments_i$ is the per-capita stimulus payments (in thousands), defined in Section 3.1. As discussed above, the variation in stimulus payments is a result of the differences in the share of population eligible for the payments across MSAs. Importantly, the eligibility and the amount of per-capita payment is largely based on household income levels before the pandemic. This fact helps alleviate concerns about correlations between stimulus payments and unobserved local economic shocks during the pandemic. However, it is possible that MSAs with different share of eligible populations happen to have experienced differential local shocks, leading to divergent house price growth during the two years. While it is impossible to completely rule out the possibility of omitted variables, I control for an extensive list of variables to ensure that the effect is not confounded by any obvious alternative factors. Standard errors are clustered at the state level, based on the location of each MSA or, for multi-state MSAs, the location of the principal city.

#### 5.1.1 Baseline controls

Table 6 reports the results of estimating Eq. (3). Column (1) shows that without any controls, the coefficient of stimulus payments is 0.046 and significant at the 5% level. Given an average household size of 2.5, the estimate implies that a \$2,500 increase in per-household payments is associated with an increase in house prices by 4.6% over the two-year period. Since most of the cross-MSA variation in payments stems from differences in the share of households eligible for the full amount, it is helpful to interpret the estimate through that lens. In a simplified scenario—where each household consists of 2.5 adults who are either fully eligible (\$3,200 per person, or \$8000 per household) or entirely ineligible—the \$1,000 per-capita difference would correspond to a 31.25 percentage-point difference in the share of households eligible for the full payment. Thus, moving from an MSA where almost no households qualified for the full \$8 000 to one where roughly one-third did is associated with a 4.6% higher price level over two years.

I next add changes in local economic conditions and population as control variables. These include changes in both transfer payments excluding stimulus checks and changes in non-transfer income in 2020 and 2021 from 2019. These other transfer payments include government social benefits and various income maintenance benefits, which experienced mostly modest increases after 2019, except for a few items such as unemployment insurance.[18] To the extent that changes in these other transfers are caused by pandemic-related or other local shocks, including these payments helps control for these shocks. In addition, the change in unemployment rate from 2019 to 2021 is also included to directly control for the severity of the COVID-19 impact on local unemployment in 2020 and the subsequent recovery in 2021. The inclusion of changes in non-transfer income helps control for any differential changes in wages and other sources of income across households of different

[18]Unemployment insurance increased by a total of around \$800 billion in 2020 and 2021, relative to the 2019 level. Other items that had nontrivial increases include social security benefits, medical benefits, and the supplemental nutrition assistance program (SNAP).

income levels during the pandemic (e.g., Autor et al., 2023).[19] Finally, the model controls for population size as of 2019 and the net population growth from 2019 to 2021 to account for pandemic-driven population migration. This is potentially important because people were more likely to move to areas with a lower cost of living during the pandemic (e.g., Haslag and Weagley, 2023), which could be associated with higher stimulus payments.

Column (2) shows that changes in other transfer income, changes in non-transfer income, and population growth are all significantly positively related to house price growth, while the change in unemployment rate from 2019 to 2021 is negatively correlated with house price growth. These variables explain a large proportion of the variation in MSA house price growth during this period, with the R-squared rising to 55%, largely driven by population growth. But controlling for these variables does not have a notable effect on the coefficient of stimulus payments, which increases slightly to 0.048 and remains statistically significant.[20] Figure 5 illustrates this positive relationship using a binned scatter plot of house price growth from 2019 to 2021 against the residuals obtained from regressing stimulus payments on these control variables.

### 5.1.2 Controlling for income per capita

As noted earlier, because high income families do not qualify for stimulus payments, the amount of per-capita payments is negatively correlated with MSA income levels. Although the estimation controls for many observed economic and demographic changes, one might still be concerned that cities with lower income levels might have experienced more positive unobserved demand shocks, leading to a greater increase in house prices. To partially address this possibility, I next include an area's pre-pandemic per-capita income as an additional control.

[19] Another related factor is variation in savings behavior across the income distribution. For example, an alternative explanation of the result is that low-income households spent less and saved more during the pandemic and used the excess savings for down payments. However, existing studies such as Chetty et al. (2023) find the contrary: high-income households cut spending much more than low-income households during the pandemic, driven by spending reductions in services that require in-person physical interactions.

[20] One might wonder whether the positive association between stimulus payments and house price growth holds for MSAs of different sizes. To test this, I divide MSAs into two groups based on the median population in 2019, which is 248,555, and then repeat the same analysis on these two groups of MSAs. Appendix Table A3 shows that the coefficient of stimulus payment for large and small MSAs is 0.045 and 0.058, respectively, both significant at the 5% level. In the last column, I use the entire sample but weight MSAs by their 2019 population. The coefficient of stimulus payment increases substantially to 0.089.

To see why this simple test helps mitigate concerns about confounding factors, consider two hypothetical cities: City A, where 100% of individuals have an AGI of $75,000, and City B, where 50% of the population has an AGI of $50,000 and the other 50% an AGI of $100,000. Although both cities have the same average AGI, everyone in City A qualifies for the payments, whereas only half of City B's population does. If stimulus payments indeed have a positive effect on housing demand and house prices, we should expect a greater increase in house prices in City A than in City B, an outcome not necessarily predicted by alternative explanations.

Column (3) shows that the coefficient of stimulus payments changes little when per-capita income is included, while per-capita income itself is not statistically significant. This result indicates that what matters is not an MSA's average income level, but rather specifically the share of population eligible for the payments.

#### 5.1.3 Additional controls

As one would expect, an MSA's median house price is strongly positively correlated with its income per capita and negatively correlated with the stimulus payments. One possible alternative explanation of the result is that during the pandemic, people moved away from expensive housing markets to more affordable housing markets, causing house prices to rise faster in places with lower housing values and greater stimulus payments. To address this possibility, the next estimation controls for the median MSA house prices as of 2019. Column (4) shows that house price growth from 2019 to 2021 is in fact significantly positively correlated with median housing value in 2019, and controlling for median housing value increases the coefficient of stimulus payments to 0.054.

The estimation so far controls for net population growth, but there may still be a concern that population growth is not enough to account for the effect of pandemic driven migration. This is because population growth reflects net migration, but large population inflows could lead to large outflows, leaving the total population relatively unchanged. Such population churn and associated housing demand may still result in significant house price appreciation. I thus next further control for total population inflow during 2020-2021 as a fraction of total population in 2019. Column (5) shows that the coefficient of inflow is indeed positive and statistically significant, and adding this control reduces the payment coefficient to 0.049.[21]

[21] One remaining concern is that population growth or migration based on changes of address in tax

Population density played a significant role in migration patterns during the pandemic (e.g., Haslag and Weagley, 2023; Gupta et al., 2022). To account for this, I include population density as an additional control. Column (6) shows that, after controlling for other factors, population density is not significantly associated with housing price growth during this period. The coefficient on stimulus payments decreases slightly to 0.045; however, this decline is entirely due to the smaller sample size resulting from missing density data for some MSAs. When the estimation is run on the same subsample with non-missing density data but excludes the density variable, the coefficient on stimulus payments remains 0.045. Given this, I do not control for density in subsequent analyses to preserve the larger sample size.

Another possibility is that MSAs with different stimulus payments were already on different house price growth trajectories prior to the pandemic, which could lead to differential house price growth in 2020 and 2021 even in the absence of differential local demand shocks during this period. I next add the lagged two-year house price growth from 2017 to 2019 as an additional control. Column (7) shows that there is indeed a high degree of house price momentum, as the lagged house price growth is highly significant and explains an additional 9% of the variation in MSA house price growth. The coefficient of stimulus payments drops to 0.044 and remains statistically significant.[22]

The next specification controls for an MSA's exposure to the WFH shift. The percentage of jobs that can be performed remotely varies widely across cities and industries (Dingel and Neiman, 2020), and prior research has shown that MSAs with a greater share of population able to work remotely experienced faster house price growth (e.g., Gupta et al., 2022; Mondragon and Wieland, 2022). It should be noted that this finding is

returns tends to reflect permanent relocation, while some people may have decided to relocate only temporarily during the pandemic. To deal with this concern, I use HMDA data to calculate the change in the fraction of mortgages labeled as secondary residence or investment property from 2019 to 2020 and 2021. Untabulated results show that this change is indeed positively correlated with changes in house prices, but adding this variable as an additional control leads to a slightly larger coefficient of stimulus payments and a larger t-stat.

[22]To further evaluate the possibility of differential housing trends, I conduct a falsification test by regressing house price growth in prior years on stimulus payments and other control variables in 2020 and 2021. Specifically, I use the same variables as in column (3) and their 2020-2021 values but change the dependent variable to house price growth during 2014-2016, 2015-2017, 2016-2018, and 2017-2019, respectively. The coefficient of stimulus payments from each regression and their 90% confidence intervals are plotted in Figure A6. All four coefficients from using house price growth prior to 2020 were close to and not significantly different from 0. The figure also suggests that when controlling for other observables, MSAs with different stimulus payments were not on different house price trends prior to 2020.

unlikely to explain the positive relationship between stimulus payments and house price growth documented in this paper. This is because individuals with lower income are more likely to work in occupations that cannot be performed at home, resulting in a negative correlation between an MSA's WFH exposure and its stimulus payments.

Column (8) reports the results where the Dingel and Neiman (2020) measure of WFH exposure is used. The exposure has a negative but statistically insignificant relation with house price growth from 2019 to 2021.[23] The coefficient of stimulus payments drops to 0.038, but remains statistically significant at the 5% level. In column (9), I follow Mondragon and Wieland (2022) and measure WFH exposure based on the share of workers in an MSA who report working from home in the 2019 ACS. The coefficient of remote work share is significantly positive, suggesting that house price grew faster in areas where a larger share of the population works remotely, consistent with the findings in Mondragon and Wieland (2022). The coefficient of stimulus payment increases to 0.058.[24]

The last model specification includes state fixed effects to compare stimulus payments and house price growth across MSAs within the same state. This specification discards substantial variation in house price growth and stimulus payments across states, as untabulated results show that state fixed effects alone can explain 60% of the variation in house price growth across MSAs during the two-year period. Nonetheless, this specification helps address concerns about unobserved shocks to a region that correlate with both stimulus payments and house price growth. Column (10) shows that the coefficient of stimulus payments declines to 0.044 but remains statistically significant at the 5% level when only variation within states is used for identification.

#### 5.1.4 Magnitude of the effect

Overall, the results show that house prices grew faster during 2020-2021 in areas where residents received a larger amount of stimulus payments on average. Extrapolating the cross-sectional estimates suggests that the stimulus payments could potentially explain a substantial portion of the observed house price appreciation. For example, multiplying

[23] Gupta et al. (2022) find that the Dingel and Neiman (2020) WFH exposure is positively related to house price growth from 2019 to 2020 among the 30 largest MSAs. If I limit the estimation to the 30 largest MSAs, the WFH variable is indeed positive and statistically significant.

[24] Untabulated results show that if the change in remote work share from 2019 to 2021 is also added as a control, it is not statistically significant, while the coefficient of stimulus payments remains virtually the same.

the point estimates from Table 6 by the per-capita EIPs and CTC payments of $2,750 yields an estimated overall impact of stimulus payments on house prices between 10% and 16%, which represents approximately one-third to one-half of the average house price increase across MSAs.

While the magnitude of the estimated effect is sizable, it is consistent with the mechanisms discussed in Section 2.2. The large stimulus payments likely relaxed borrowing constraints for a significant share of the population. This direct effect may have been further amplified by lower mortgage rates and shifting expectations of future house prices. The estimate is also in line with prior evidence on the substantial impact of relaxing loan-to-value (LTV) constraints on housing demand and prices (e.g., Gupta et al., 2023; Greenwald and Guren, 2024). In the context of transfer payments, Berger et al. (2023) use a quantitative life-cycle model to show that such payments can have sizable effects on housing demand. Their calibration indicates that a $1,000-per-household transfer leads to more than a 30% increase in housing transactions and investment over a three-year period, largely driven by the easing of down payment constraints among marginal home buyers.

## 5.2 Extensions and robustness

### 5.2.1 Timing of the effect

The analyses in the previous section focus on the growth in house prices during the entire two-year period of 2020 and 2021. To shed light on the timing of house price adjustments, I next examine the evolution of house prices at the monthly frequency over the two-year period. Specifically, I calculate the growth rate of house prices for each month in 2020 and 2021 from December 2019 and regress the growth rate on the per-capita stimulus payments in 2020-2021 and the baseline control variables used in column (2) of Table 6.

Figure 6 plots the coefficient estimates of stimulus payments and the 90% confidence intervals for each month within the two-year period. The gray bars in the figure represent the timing of the three rounds of EIPs, with the height of the bars indicating the magnitude of total payments for each round, including the nearly $100 billion CTC distributed in 2021. The figure shows that there is little divergence in house price growth across MSAs with differing levels of stimulus payments in 2020. House prices in high-payments MSAs begin to grow more rapidly in early 2021 and the coefficient becomes statistically significant in the later half of the year. The coefficient continues to increase throughout the remainder of the year, reaching 0.048 by December 2021.

### 5.2.2 Stimulus payments excluding the CTC

Because of the advance payments of the CTC in 2021, the per-capita stimulus payment calculated in Eq. (1) is positively correlated with the share of young children across MSAs. A potential issue is that families with young children may have experienced a greater increase in housing demand for reasons unrelated to the stimulus payments, leading to an upward bias in estimating the effect of stimulus payments on house prices.

To address this concern, I create a measure of EIPs by excluding the advance payments of the CTC from the stimulus payment measure in 2021. This is done by estimating the amount of advance payments based on the share of the population eligible for these advance CTC payments, using Census age data, and then subtracting the estimated amount from the total refundable tax credits reported in the BEA data in 2021.[25]

Table A4 replicates the analyses in Table 6 using this adjusted measure of stimulus payments. The point estimates are slightly larger across all model specifications, suggesting a stronger association between per-capita EIPs and house price growth.

### 5.2.3 Persistence of the effect

This paper focuses on housing market activity during the 2020–2021 period when stimulus payments were made. Naturally, one might wonder how house prices evolved beyond 2021. If some households' housing demand responded to the stimulus payments with a delay, we could see continued effects beyond 2021. However, if the large transitory income shocks brought future demand forward by relaxing financial constraints, we might expect to see a reversal in the effect.

Figure 7 extends the analysis in Section 5.2.1 through 2024. It shows that house prices in high-payment MSAs continued to appreciate relative to low-payment MSAs for several months into 2022, before plateauing for the rest of 2022 and 2023. One possible explanation for the persistence of this effect is that the initial boom may have shifted investors' expectations about the future trajectory of house prices, sustaining demand in high-payment areas (Chi et al., 2023). Starting in 2024, however, a clear reversal

[25] The amount of advance payment was $1,800 for children under 6 and $1,500 for children aged 6 to 17.

emerges. By mid-2024, the estimated effect drops below its late-2021 level, and large standard errors make it statistically indistinguishable from zero. This partial reversal aligns with the notion that large transitory income shocks can boost housing demand and prices by partly pulling demand forward from the future.

#### 5.2.4 Within-MSA estimation

The analyses presented so far examine the relationship between house price growth and stimulus payments across MSAs. In this section, I turn to a within-MSA analysis by comparing variation across counties within the same MSA, which helps control for unobserved shocks at the broader metropolitan level. While this approach mitigates MSA-level confounding factors, it is subject to within-MSA dynamics—particularly intra-city migration, which has been shown to significantly influence local housing markets (e.g., Gupta et al., 2022; Ramani and Bloom, 2022). To account for these effects, I control for population inflows, the share of the population living in urbanized areas, population density, and each county's distance to the Central Business District (CBD) of the MSA. For this analysis, I use FHFA house price data, as Freddie Mac data are not available at the county level.[26] Following Ramani and Bloom (2022), I obtain CBD locations from Holian (2019).

Appendix Table A5 presents the results. Column (1) reports estimates without MSA fixed effects, using only counties within multi-county MSAs. The coefficient of stimulus payments is 0.043 and significant at the 1% level. In column (2), when MSA fixed effects are included, the coefficient decreases slightly to 0.038 and remains significant at the 1% level. These results suggest that the positive relationship between house price growth and stimulus payments is not driven by unobserved common shocks at the MSA level.

#### 5.2.5 Alternative house price indices

The MSA level analyses above rely on house prices from the Freddie Mac House Price Index. The county-level analyses in the previous section show that the results are robust

[26] The FHFA indices, like the FMHPI, are repeat-sale indices based on transactions of single-family properties with mortgages purchased or securitized by Fannie Mae or Freddie Mac. As a result, the two indices exhibit a high correlation (0.95). However, notable differences in MSA-level house price growth rates occasionally arise between them. One key distinction is that the FHFA indices use an equal-weighting scheme, whereas the FMHPI indices are value-weighted. From 2019 to 2021, the average county-level house price growth was 14%, which is slightly less than half the growth rate of the FMHPI across MSAs, as reported in Table 1.

when using the FHFA House Price Index. However, both indices cover only single-family properties. A potential concern is that there may be systematic differences in house price appreciation between single-family homes and other types of properties, such as condos. If the composition of property types varies systematically with the amount of stimulus payments across MSAs, this could introduce bias into the estimates.

To address this concern, I turn to the Zillow Home Value Index (ZHVI), which captures price trends for all types of homes. Figure A9 presents the results of the same analysis as in Section 5.2.3, but based on Zillow home prices. The results are broadly similar, although the estimated effects using Zillow data appear to lag by a few months relative to those based on Freddie Mac data.

## 5.3 Stimulus payments and other housing outcomes

This section extends the analysis beyond house prices to explore additional housing market outcomes, including the number of housing units, new listings, transaction volumes, and mortgage terms.

First, I use the number of new privately-owned housing units authorized by building permits as a proxy for housing starts and changes in housing stock. I regress the total number of housing permits issued in an MSA in 2020 and 2021 divided by the number of housing units in 2019 on per-capita stimulus payments and control variables. Column (1) of Table 7 reports that the coefficient of stimulus payment is $-0.005$ and significant at the 5% level, suggesting that areas receiving higher payments experienced slower housing unit growth. As shown in column (2), however, adding unit growth as a control variable in the house price regression has little impact on the stimulus payment estimate, while the unit growth coefficient itself is negative but not statistically significant.

Under certain assumptions, one can create a measure of shift in housing demand using changes in house prices and housing units. Specifically, assuming a log-linear demand for housing and a unit elasticity of housing demand, the local shift in housing demand can be measured simply by the sum of house price growth and housing unit growth (Charles et al., 2018). Column (3) shows that stimulus payments have a significantly positive effect on the sum of house price and unit growth, with a magnitude similar to those on house price growth reported in Table 6.

In addition to new housing construction, constrained housing supply may also result from a reduced flow of existing homes to the market. To explore this possibility, I examine changes in the number of new home listings. Specifically, I calculate the growth in new listings in 2020 and 2021 relative to 2019 and compare this growth across MSAs with varying levels of stimulus payments. Column (6) shows that the coefficient on stimulus payments is positive and statistically significant, indicating that high-payment MSAs experienced relatively larger increases in new listings. This result provides further evidence that the observed increase in house prices in high-payment areas was not driven by reduced housing supply. Column (7) shows that controlling for changes in listings increases the estimated coefficient on stimulus payments in the house price regression to 0.051.

I next turn to the HMDA data to examine the volume of housing transactions and the dynamics of mortgage terms. I use the number of home purchase mortgages originated at the MSA level as a proxy for home purchase activities. The increase in mortgage originations from 2019 to 2020 and 2021 is regressed on stimulus payments and control variables. Column (1) of Table 8 reports that the coefficient of stimulus payments is 0.11 and is significant at the 1% level, indicating that a $1,000 extra payment per person is associated with a 11% increase in mortgage-financed home purchases over the two-year span. The heightened housing transaction volume may be attributed to first-time home buyers entering into homeownership, as previously documented, and to existing homeowners benefiting from eased down payment constraints due to rising house prices, as highlighted by Stein (1995).

I next examine mortgage terms in the HMDA data, focusing on several key indicators: the loan-to-value ratio, loan-to-income ratio, denial rate, and mortgage rate spread. Denial rate is defined as the fraction of home purchase loan applications that are not approved. The rate spread reported in the HMDA data is the difference between a loan's annual percentage rate and the average prime offer rate for a comparable type mortgage. For each variable, I calculate the changes within MSAs by comparing the average of 2020 and 2021 values to the baseline in 2019.

Columns (2) and (3) show that stimulus payments are not associated with significant changes in either loan to value ratio or loan to income ratio.[27] However, column (4) shows

[27] The lack of significant changes in MSA-level LTI ratios may seem at odds with the household-level finding that lower-income borrowers experienced a significant relative increase in LTI ratios. However, these results are not necessarily contradictory. This is because housing transactions typically rise across income groups within a region—including among existing homeowners, who tend to have lower LTI ratios on new mortgages. In high-payment areas, increased demand from lower-income first-time buyers

that areas with greater stimulus payments experience a significant increase in mortgage denial rate. These results suggest that the increase in home purchases in high payment areas is not driven by an expansion in the supply of mortgage credit. The last column shows that high payment areas experience a significant decline in rate spread; however, the magnitude of the effect is modest: an additional one-thousand dollar per-capita payment is associated with a decline in rate spread by about 6 basis points.

Overall, the results in this section provide further support for the interpretation that the observed house price increases in high-payment areas were primarily driven by heightened demand, rather than by confounding factors such as differential shocks to housing supply or mortgage credit availability.

# 6 Conclusion

This paper examines the impact of the historic fiscal stimulus payments during the COVID-19 pandemic on the U.S. housing market. The three rounds of payments were significant relative to the average household savings and typical down payments made by home buyers. I find that lower-income households—who experienced a significant increase in disposable income due to stimulus payments—saw greater increases in homeownership rates and housing consumption. Exploiting the phased reduction in payment amounts above specific income thresholds provides further evidence of a positive effect of these payments on housing demand. At the city level, areas with a larger share of the population eligible for the payments experienced faster appreciation of house prices and greater housing transactions. These effects cannot be explained by other observed economic or demographic shocks during the pandemic, nor by differential changes in housing supply or credit conditions.

To the best of my knowledge, this paper provides the first empirical evidence that stimulus checks had a significant impact on household housing demand and broader housing market dynamics. Prior studies on consumer spending from stimulus payments do not consider housing purchases. The findings in this paper suggest that excluding housing may substantially underestimate the overall impact of fiscal stimulus, particularly for

and the accompanying rise in house prices could have triggered additional transactions among existing homeowners through a "housing chain" effect. Since these existing homeowners often have lower LTI ratios, their increased presence in the transaction pool could offset the higher LTI ratios among first-time buyers, muting the aggregate change in LTI ratios observed at the MSA level.

payments of large sizes. Housing-related spending and residential investment triggered by increased housing demand could be an important channel through which the transfer payments stimulate the economy. Rising house prices could lead to further spending through a housing wealth effect. In addition, the findings also support the view that the fiscal stimulus and relief efforts helped contribute to the housing boom during the pandemic and the elevated inflation not seen since the early 1980s.

# References


Adelino, M., Schoar, A., Severino, F., 2016. Loan Originations and Defaults in the Mortgage Crisis: The Role of the Middle Class. The Review of Financial Studies 29, 1635–1670.

Adelino, M., Schoar, A., Severino, F., 2018. Dynamics of housing debt in the recent boom and great recession. NBER Macroeconomics Annual 32, 265–311.

Adelino, M., Schoar, A., Severino, F., 2024. Credit supply and house prices: evidence from mortgage market segmentation. Journal of Financial Economics, forthcoming .

Agarwal, S., Liu, C., Souleles, N., 2007. The reaction of consumer spending and debt to tax rebates—evidence from consumer credit data. Journal of Political Economy 115, 986–1019.

Albanesi, S., DeGiorgi, G., Nosal, J., 2022. Credit growth and the financial crisis: A new narrative. Journal of Monetary Economics 132, 118–139.

Autor, D., Cho, D., Crane, L.D., Goldar, M., Lutz, B., Montes, J., Peterman, W.B., Ratner, D., Villar, D., Yildirmaz, A., 2022. The $800 billion paycheck protection program: Where did the money go and why did it go there? Journal of Economic Perspectives 36, 55–80.

Autor, D., Dube, A., McGrew, A., 2023. The unexpected compression: Competition at work in the low wage labor market. Technical Report. National Bureau of Economic Research.

Baker, S., Farrokhnia, R.A., Meyer, S., Pagel, M., Yannelis, C., 2023. Income, Liquidity, and the Consumption Response to the 2020 Economic Stimulus Payments. Review of Finance , rfad010.

Bartik, A.W., Cullen, Z.B., Glaeser, E.L., Luca, M., Stanton, C.T., Sunderam, A., 2020. The targeting and impact of Paycheck Protection Program loans to small businesses. Technical Report. National Bureau of Economic Research.

Beraja, M., Zorzi, N., 2023. Durables and size-dependence in the marginal propensity to spend .

Berger, D., Cui, T., Turner, N., Zwick, E., 2023. Stimulating durable purchases: Theory and evidence .

Berger, D., Turner, N., Zwick, E., 2020. Stimulating housing markets. The Journal of Finance 75, 277–321.

Blanchet, T., Saez, E., Zucman, G., 2022. Real-time inequality. Technical Report. National Bureau of Economic Research.

Brueckner, J., Kahn, M.E., Lin, G.C., 2021. A New Spatial Hedonic Equilibrium in the Emerging Work-from-Home Economy? Working Paper 28526. National Bureau of Economic Research.

Calonico, S., Cattaneo, M.D., Titiunik, R., 2014. Robust nonparametric confidence intervals for regression-discontinuity designs. Econometrica 82, 2295–2326.

Charles, K.K., Hurst, E., Notowidigdo, M.J., 2018. Housing booms and busts, labor market opportunities, and college attendance. American Economic Review 108, 2947–94.

Chetty, R., Friedman, J.N., Stepner, M., et al., 2023. The Economic Impacts of COVID-19: Evidence from a New Public Database Built Using Private Sector Data. The Quarterly Journal of Economics , qjad048.

Chi, C.C., LaPoint, C., Lin, M.J., 2023. Spatially targeted LTV policies and collateral values. Available at SSRN 4426887 .

Chodorow-Reich, G., Guren, A.M., McQuade, T.J., 2022. The 2000s housing cycle with 2020 hindsight: A neo-kindlebergerian view. Review of Economic Studies, forthcoming .

Clemens, J., Hoxie, P.G., Veuger, S., 2022. Was Pandemic Fiscal Relief Effective Fiscal Stimulus? Evidence from Aid to State and Local Governments. Technical Report. National Bureau of Economic Research.

Coibion, O., Gorodnichenko, Y., Weber, M., 2020. How did US consumers use their stimulus payments? Technical Report. National Bureau of Economic Research.

Cox, N., Ganong, P., Noel, P., Vavra, J., Wong, A., Farrell, D., Greig, F., Deadman, E., 2020. Initial impacts of the pandemic on consumer behavior: Evidence from linked income, spending, and savings data. Brookings Papers on Economic Activity 2020, 35–82.

Di Maggio, M., Kermani, A., 2017. Credit-Induced Boom and Bust. The Review of Financial Studies 30, 3711–3758.

Diamond, W., Landvoigt, T., Sanchez, G., 2023. Printing away the mortgages: Fiscal inflation and the post-Covid housing boom. Available at SSRN .

Dingel, J.I., Neiman, B., 2020. How many jobs can be done at home? Journal of Public Economics 189, 104235.

Drechsler, I., Savov, A., Schnabl, P., 2022. How monetary policy shaped the housing boom. Journal of Financial Economics 144, 992–1021.

Favara, G., Imbs, J., 2015. Credit supply and the price of housing. American Economic Review 105, 958–92.

Favilukis, J., Ludvigson, S.C., Van Nieuwerburgh, S., 2017. The macroeconomic effects of housing wealth, housing finance, and limited risk sharing in general equilibrium. Journal of Political Economy 125, 140–223.

Flavin, M., Nakagawa, S., 2008. A model of housing in the presence of adjustment costs: A structural interpretation of habit persistence. American Economic Review 98, 474–95.

Fuster, A., Zafar, B., 2021. The sensitivity of housing demand to financing conditions: Evidence from a survey. American Economic Journal: Economic Policy 13, 231–65.

Gamber, W., Graham, J., Yadav, A., 2022. Stuck at home: Housing demand during the COVID-19 pandemic. Journal of Housing Economics, forthcoming .

Ganong, P., Greig, F., Noel, P., Sullivan, D.M., Vavra, J., 2024. Spending and job-finding impacts of expanded unemployment benefits: Evidence from administrative micro data. American Economic Review 114, 2898–2939.

Ganong, P., Noel, P., Vavra, J., 2020. US unemployment insurance replacement rates during the pandemic. Journal of Public Economics 191, 104273.

Glaeser, E., Gottlieb, J., Gyourko, J., 2012. Can cheap credit explain the housing boom?, in: Housing and the Financial Crisis. National Bureau of Economic Research, Inc, pp. 301–359.

Glaeser, E.L., Gyourko, J., Saiz, A., 2008. Housing supply and housing bubbles. Journal of Urban Economics 64, 198–217.

Granja, J., Makridis, C., Yannelis, C., Zwick, E., 2022. Did the paycheck protection program hit the target? Journal of Financial Economics 145, 725–761.

Greenwald, D.L., Guren, A., 2024. Do credit conditions move house prices? Amercian Economic Review, forthcoming .

Griffin, J.M., Kruger, S., Mahajan, P., 2023. Did pandemic relief fraud inflate house prices? Available at SSRN .

Gupta, A., Hansman, C., Mabille, P., 2023. Financial constraints and the racial housing gap .

Gupta, A., Mittal, V., Peeters, J., Van Nieuwerburgh, S., 2022. Flattening the curve: pandemic-induced revaluation of urban real estate. Journal of Financial Economics 146, 594–636.

Han, L., 2010. The effects of price risk on housing demand: Empirical evidence from u.s. markets. The Review of Financial Studies 23, 3889–3928.

Haslag, P., Weagley, D., 2023. From L.A. to Boise: How migration has changed during the COVID-19 pandemic. Journal of Financial and Quantitative Analysis , 1–31.

Holian, M.J., 2019. Where is the city's center? five measures of central location. Cityscape 21, 213–226.

Howard, G., Liebersohn, J., Ozimek, A., 2023. The short- and long-run effects of remote work on U.S. housing markets. Journal of Financial Economics 150, 166–184.

Hsu, J.W., Matsa, D.A., Melzer, B.T., 2018. Unemployment insurance as a housing market stabilizer. American Economic Review 108, 49–81.

Johnson, D.S., Parker, J.A., Souleles, N.S., 2006. Household expenditure and the income tax rebates of 2001. American Economic Review 96, 1589–1610.

Justiniano, A., Primiceri, G., Tambalotti, A., 2019. Credit supply and the housing boom. Journal of Political Economy 127, 1317–1350.

Kaplan, G., Mitman, K., Violante, G.L., 2020. The housing boom and bust: Model meets evidence. Journal of Political Economy 128, 3285–3345.

Kaplan, G., Violante, G.L., 2014. A model of the consumption response to fiscal stimulus payments. Econometrica 82, 1199–1239.

Laibson, D., Maxted, P., Moll, B., 2023. A Simple Mapping from MPCs to MPXs. Working Paper 29664. National Bureau of Economic Research.

Landvoigt, T., Piazzesi, M., Schneider, M., 2015. The housing market(s) of san diego. American Economic Review 105, 1371–1407.

Larrimore, J., Mortenson, J., Splinter, D., 2022. Earnings shocks and stabilization during COVID-19. Journal of Public Economics 206, 104597.

Mian, A., Sufi, A., 2009. The Consequences of Mortgage Credit Expansion: Evidence from the U.S. Mortgage Default Crisis. The Quarterly Journal of Economics 124, 1449–1496.

Mian, A., Sufi, A., 2021. Credit Supply and Housing Speculation. The Review of Financial Studies 35, 680–719.

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

Määttänen, N., Terviö, M., 2014. Income distribution and housing prices: An assignment model approach. Journal of Economic Theory 151, 381–410.

Ortalo-Magné, F., Rady, S., 2006. Housing market dynamics: On the contribution of income shocks and credit constraints. The Review of Economic Studies 73, 459–485.

Parker, J.A., Schild, J., Erhard, L., Johnson, D., 2022. Economic impact payments and household spending during the pandemic. Brookings Papers on Economic Activity .

Parker, J.A., Souleles, N.S., Johnson, D.S., McClelland, R., 2013. Consumer spending and the economic stimulus payments of 2008. American Economic Review 103, 2530–2553.

Ramani, A., Bloom, N., 2022. The Donut effect of COVID-19 on cities. Technical Report. National Bureau of Economic Research.

Romer, C.D., 2021. The fiscal policy response to the pandemic. Brookings Papers on Economic Activity , 89–110.

Ruggles, S., Flood, S., Sobek, M., Backman, D., Chen, A., Cooper, G., Richards, S., Rogers, R., Schouweiler, M., 2023. IPUMS USA: Version 14.0 [dataset]. Minneapolis, MN: IPUMS.

Shapiro, M.D., Slemrod, J., 2003. Consumer response to tax rebates. American Economic Review 93, 381–396.

Stanton, C.T., Tiwari, P., 2021. Housing consumption and the cost of remote work. Technical Report. National Bureau of Economic Research.

Stein, J.C., 1995. Prices and trading volume in the housing market: A model with down-payment effects. The Quarterly Journal of Economics 110, 379–406.

Wilson, S.G., Plane, D.A., Mackun, P.J., Fischetti, T.R., Goworowska, J., 2012. Patterns of Metropolitan and Micropolitan Population Change: 2000 to 2010. Technical Report C2010SR-01. U.S. Census Bureau.

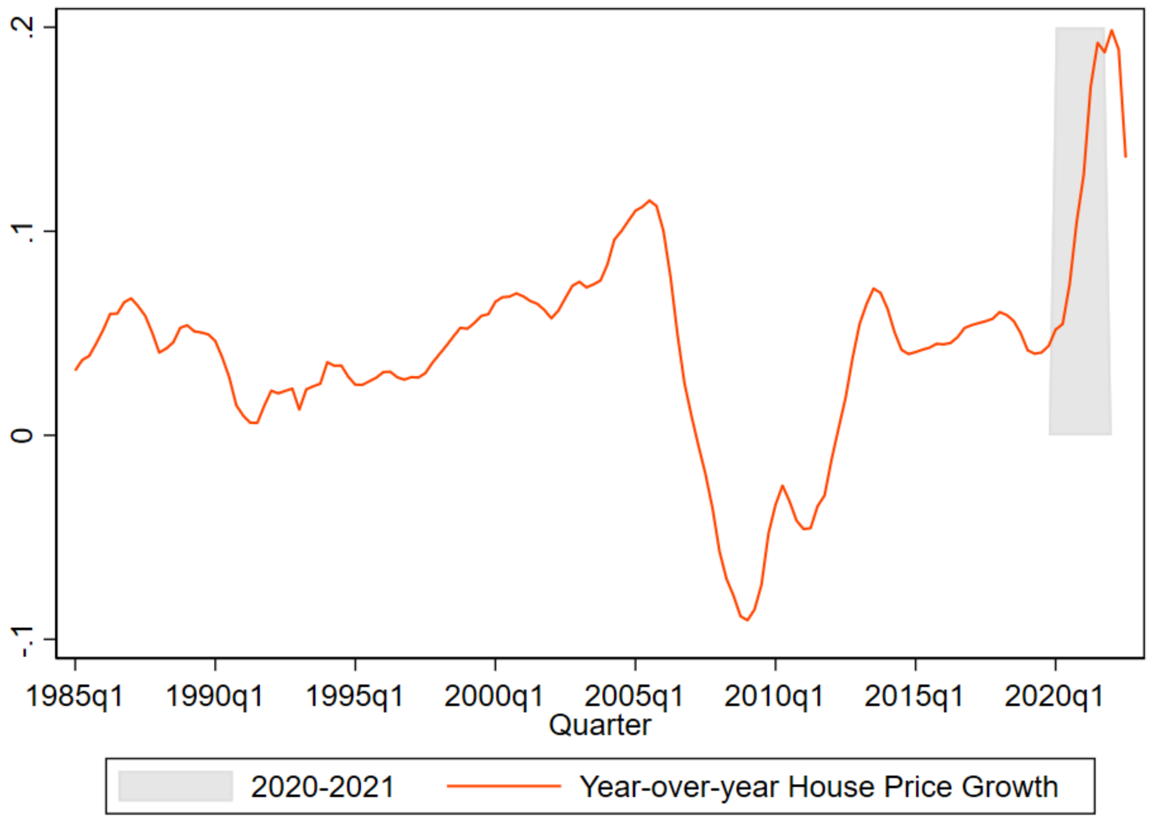
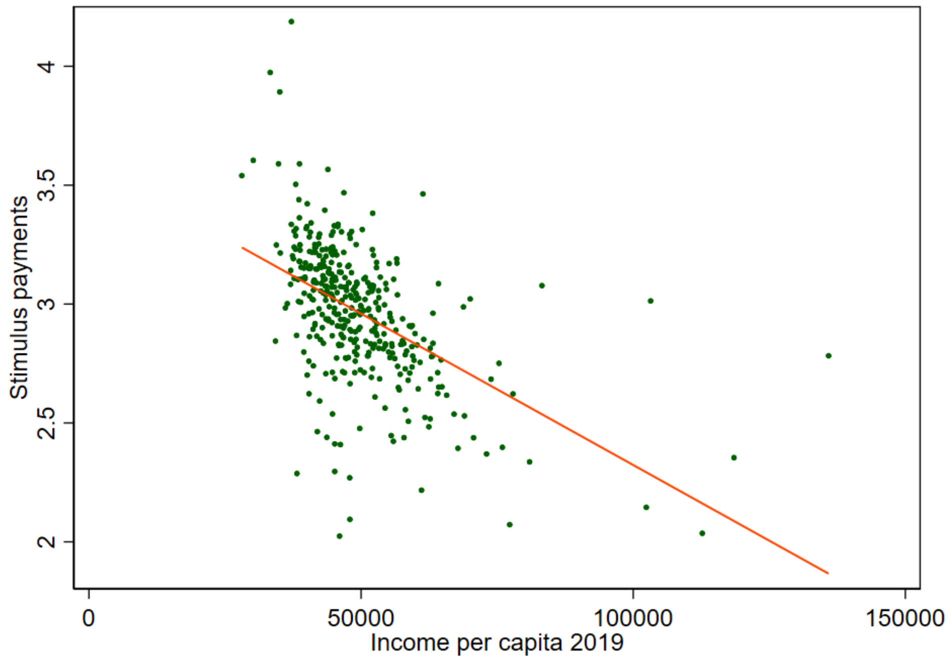
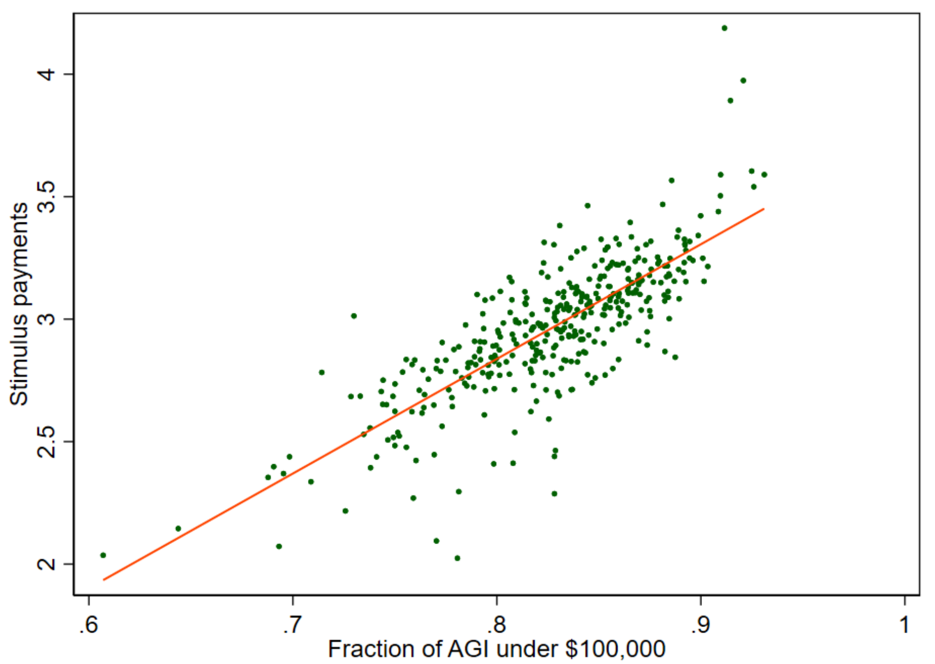



Figure 1: National house price growth 1985-2022. This figure plots the quarterly year-over-year growth in house prices from 1985 to the third quarter of 2022. The house price index data are from Fannie Mae.




(a)




(b)

Figure 2: Stimulus payments and income levels across MSAs. Panel (a) plots the per-capita stimulus payments of 2020 and 2021 against per-capita income in 2019. Panel (b) plots the per-capita stimulus payments of 2020 and 2021 against the fraction of tax returns with adjusted gross income below $100,000.

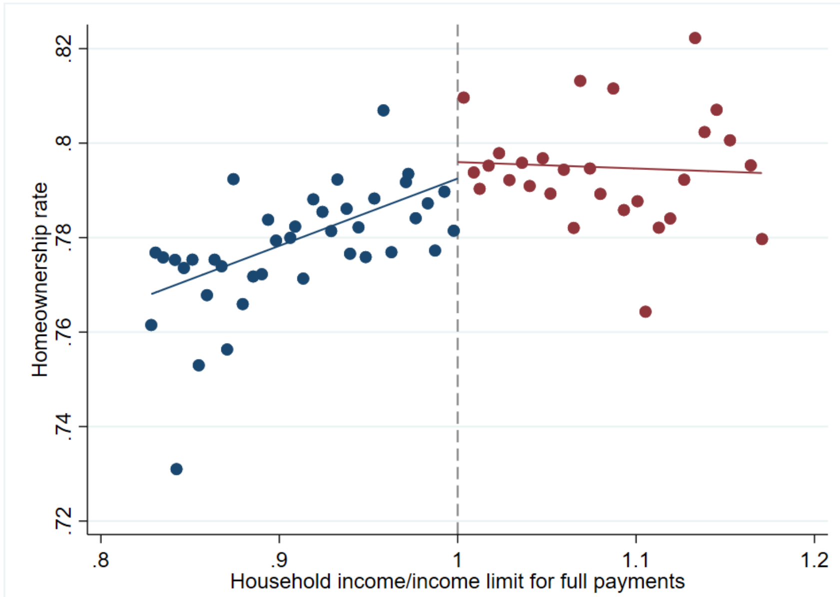


Figure 3: Household income and homeownership status in 2021. This figure presents a binned scatter plot of homeownership status and household income relative to the income limits for full stimulus payments. These income limits are $150,000 for families with a married couple and $75,000 for families without any couple or children under 19. Homeownership has been residualized from family size, age group, and married-couple indicators.

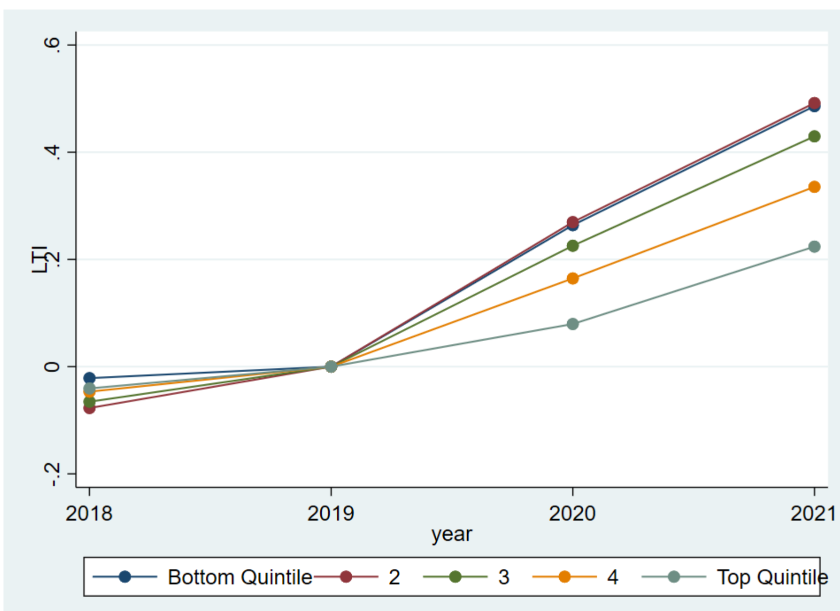


Figure 4: Loan to income ratio by income quintile. This figure plots the average loan to income ratio from 2018 and 2021 relative to 2019 for each income quintile.

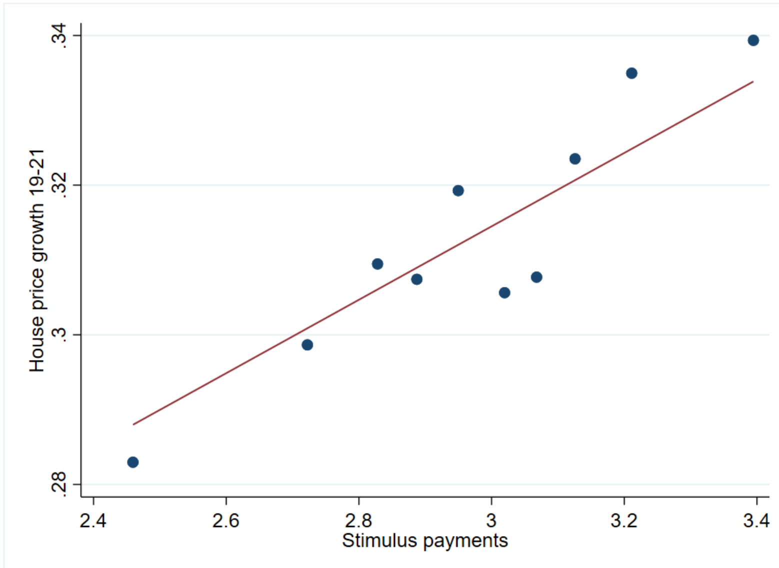



Figure 5: House price growth and stimulus payments. This figure shows the binned scatter plot of house price growth from 2019 to 2021 against the residuals from regressing stimulus payments on the control variables included in column (2) of Table 6: changes in other transfers, changes in non-transfer income, changes in unemployment rate, population growth from 2019 to 2021, and log population in 2019.

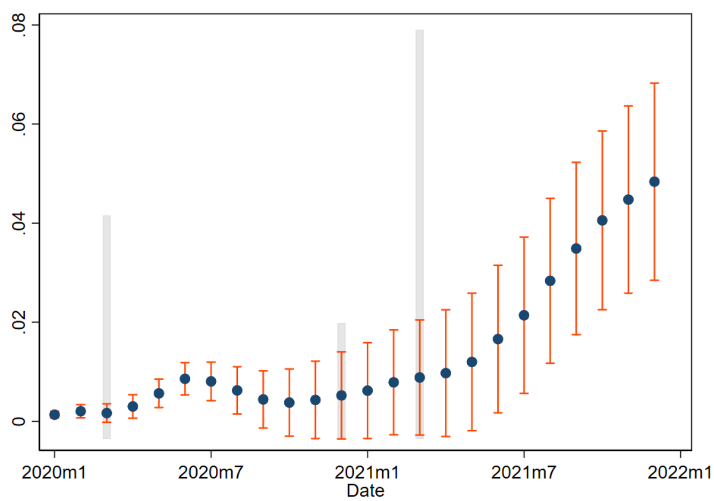



Figure 6: Monthly house prices and stimulus payments of 2020 and 2021. House price growth from December 2019 to each of the subsequent month in 2020 and 2021 is regressed on the 2020–2021 stimulus payments and control variables in column (2) of Table 6. The figure plots the coefficient of *stimulus payments* and the 90% confidence interval from each of the 24 regressions. The gray bars indicate the months when the three round of EIPs started to be disbursed. The height of the bar indicates the size of each payment.

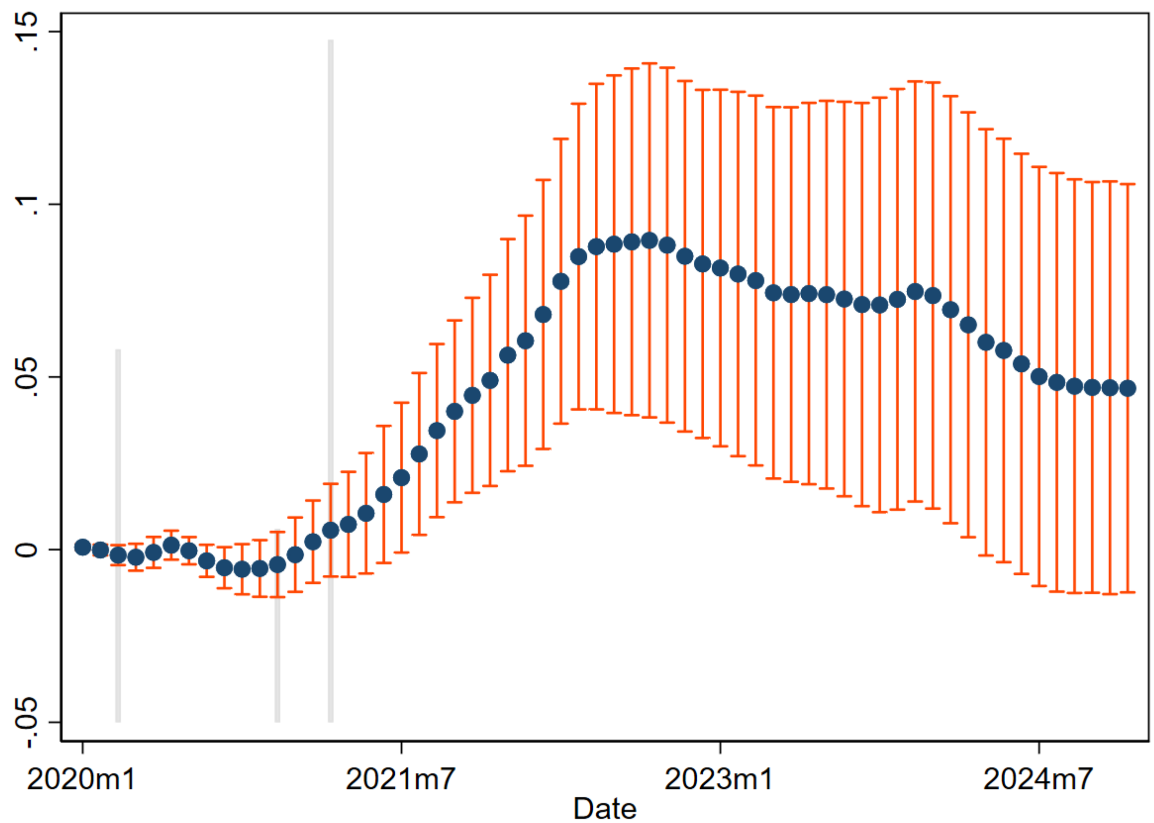



Figure 7: Evolution of house prices through 2024. House price growth from December 2019 to each of the subsequent month through December 2024 is regressed on the 2020–2021 stimulus payments and all the control variables in Table 6. The figure plots the coefficient of *stimulus payments* and the 90% confidence interval from each of the regressions.

Table 1: Summary Statistics

Panel A reports the summary statistics of household- or mortgage-level variables. *Family income* is the reported family income in the ACS data. *Ownership* is an indicator for whether the household owns its residence. *Rooms* and *Rooms per person* are the number of rooms and the number of rooms per household member, respectively. *Family size* is the number of family members in the housing unit. *Head age* is the age of the household head. $LTI$ is the amount of mortgages relative to reported income, based on HMDA data. Panel B reports the summary statistics of the MSA-level variables. $\Delta HP$ is the house price growth rate from 2019 to 2021. *Stimulus payments* is the total per-capita economic impact payments of 2020 and 2021 and the child tax credit payments of 2021 (in thousands). $\Delta$ *Other transfer* is the total increase in other transfers per capita from 2019 to 2020 and 2021 (in thousands). $\Delta$*Non transfer* is the total increase in per-capita non-transfer income from 2019 to 2020 and 2021 (in thousands). $\Delta Pop$ is the growth rate of total population from 2019 to 2021. $\Delta$*Unemp rate* is the change in unemployment rate from 2019 to 2021. $Ln(Pop_{2019})$ is the log population in 2019. $IPC_{2019}$ is the per-capita income in 2019 (in thousands). $Median\ Hvalue_{2019}$ is the median value of owner occupied housing units in 2019 (in thousands). $Pop\,inflow$ is the inflow of population from outside of the MSA in 2020 and 2021 divided by population in 2019. *Density* is the population-weighted density from the 2010 Census. $Under100_{2019}$ is the fraction of tax returns with adjusted gross income below $100,000 in 2019. $WFH$ is the fraction of jobs that can be performed entirely from home, as estimated by Dingel and Neiman (2020). *Remote share*$_{2019}$ is the share of workers that work at home in 2019 according to the ACS data. $\Delta Homeownership$ is the change in homeownership rate from 2019 to 2021. $\Delta Units$ is the growth rate of housing units. $\Delta Listing$ is the growth of total number of new listings in 2020 and 2021 from 2019. $\Delta Mortgages$ is the growth rate of originated home-purchase mortgages from 2019 to 2020 and 2021.

| | Mean | SD | Min | p50 | Max | No. of obs |
|---|---|---|---|---|---|---|
| Panel A: Household- and mortgage-level data | | | | | | |
| *Family income* | 97,692 | 106,406 | 1 | 69,400 | 2,907,600 | 3,362,299 |
| *Ownership* | 0.731 | 0.443 | 0.000 | 1.000 | 1.000 | 3,362,299 |
| *Rooms* | 6.208 | 2.489 | 1.000 | 6.000 | 21.000 | 3,362,299 |
| *Rooms per person* | 3.290 | 1.963 | 0.071 | 3.000 | 21.000 | 3,362,299 |
| *Family size* | 2.383 | 1.382 | 1.000 | 2.000 | 20.000 | 3,362,299 |
| *Head age* | 55.604 | 17.088 | 15.000 | 57.000 | 96.000 | 3,362,299 |
| $LTI$ | 2.974 | 1.547 | 0.000 | 2.863 | 29.833 | 9,501,567 |

| | Mean | SD | Min | p50 | Max | No. of obs |
|---|---|---|---|---|---|---|
| Panel B: MSA-level data | | | | | | |
| $\Delta HP$ | 0.313 | 0.090 | 0.021 | 0.303 | 0.609 | 382 |
| $Stimulus\ payments$ | 2.965 | 0.281 | 2.024 | 2.986 | 4.188 | 382 |
| $\Delta Other\ transfer$ | 4.315 | 1.433 | 1.248 | 4.121 | 9.925 | 382 |
| $\Delta Non\ transfer$ | 3.015 | 4.073 | -56.119 | 3.007 | 25.297 | 382 |
| $\Delta Pop$ | 0.008 | 0.018 | -0.051 | 0.005 | 0.090 | 382 |
| $\Delta Unemp\ rate$ | 0.527 | 0.977 | -4.900 | 0.400 | 3.900 | 382 |
| $Ln(Pop_{2019})$ | 12.698 | 1.086 | 10.931 | 12.423 | 16.772 | 382 |
| $IPC_{2019}$ | 49.524 | 11.455 | 28.091 | 47.135 | 135.900 | 382 |
| $Median\ Hvalue_{2019}$ | 204.916 | 112.254 | 79.900 | 171.100 | 968.800 | 382 |
| $Pop\, inflow$ | 0.049 | 0.024 | 0.014 | 0.045 | 0.124 | 382 |
| $Density$ | 2,398 | 2,248 | 522 | 1,907 | 31,251 | 358 |
| $Under100_{2019}$ | 0.827 | 0.047 | 0.607 | 0.833 | 0.931 | 382 |
| $WFH$ | 0.325 | 0.055 | 0.193 | 0.314 | 0.519 | 382 |
| $Remote\ share_{2019}$ | 0.051 | 0.020 | 0.010 | 0.048 | 0.130 | 382 |
| $\Delta Homeownership$ | 0.011 | 0.025 | -0.106 | 0.011 | 0.087 | 382 |
| $\Delta Units$ | 0.024 | 0.019 | 0.000 | 0.019 | 0.112 | 382 |
| $\Delta Listing$ | -0.070 | 0.089 | -0.365 | -0.069 | 0.539 | 382 |
| $\Delta Mortgages$ | 0.278 | 0.168 | -0.297 | 0.262 | 0.945 | 382 |

Table 2: Changes in real household income by income group, 2019–2021

The table shows real income growth in 2020 and 2021 relative to 2019 for households in the top 10%, middle 40%, and bottom 50% of the income distribution. Income growth is calculated as the combined increase in income from 2019 to 2020 and from 2019 to 2021, divided by 2019 income. Factor income refers to income from labor and capital, before any tax and government transfers. Pretax income is factor income minus pension contributions, plus pension benefits, disability insurance, and unemployment insurance. Disposable is pretax income minus taxes, plus government transfers. Source: Blanchet et al. (2022)

| | Factor income | Pretax income | Disposable income |
|---|---|---|---|
| Bottom 50% | -7.7% | 3.1% | 32.0% |
| Middle 40% | -2.2% | 1.3% | 18.8% |
| Top 10% | 0.3% | -4.2% | 1.3% |

Table 3: Changes in housing consumption by income groups

In the first three columns, the dependent variable is an indicator variable for owning the housing unit. In the column (4), the dependent variable is the number of rooms in the housing unit and (5)-(7) the number of rooms per person. $Quintile\,1-4$ are indicators for family income quintiles in each year. $Post$ is an indicator variable for year 2020 and 2021. Control variables include the age of the household head and the size of the household. The sample period is from 2019 to 2021. Observations are weighted by household weights included in the ACS data. Standard errors are clustered by the state in which the household is located.

| | Homeownership | | | Number of rooms | | | |
|---|---|---|---|---|---|---|---|
| | | | | Total | Per person | | |
| | | | | | All | Homeowners | Renters |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| $Quintile\ 1 \times post$ | 0.011*** | 0.018*** | 0.022*** | 0.078*** | 0.054*** | 0.041*** | 0.009 |
| | (0.002) | (0.002) | (0.002) | (0.011) | (0.008) | (0.011) | (0.017) |
| $Quintile\ 2 \times post$ | 0.009*** | 0.014*** | 0.015*** | 0.058*** | 0.025*** | 0.023*** | -0.003 |
| | (0.002) | (0.002) | (0.002) | (0.010) | (0.007) | (0.008) | (0.016) |
| $Quintile\ 3 \times post$ | 0.005*** | 0.008*** | 0.008*** | 0.048*** | 0.009 | 0.009 | -0.004 |
| | (0.002) | (0.002) | (0.002) | (0.010) | (0.006) | (0.006) | (0.012) |
| $Quintile\ 4 \times post$ | 0.002 | 0.003 | 0.004* | 0.034*** | 0.006 | 0.005 | -0.009 |
| | (0.002) | (0.002) | (0.002) | (0.011) | (0.007) | (0.007) | (0.014) |
| Quintile dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Controls*post | No | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | No | No | No | No | No |
| County*year FE | No | No | Yes | Yes | Yes | Yes | Yes |
| R-squared | 0.210 | 0.211 | 0.255 | 0.267 | 0.412 | 0.480 | 0.350 |
| N | 3362299 | 3362299 | 3362299 | 3362299 | 3362299 | 2459272 | 903027 |

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Income and homeownership around stimulus payment income thresholds

In Panel A, the dependent variable is an indicator equal to 1 if the housing unit is owned, and 0 if rented. In Panel B, the dependent variable is the number of rooms per person in the housing unit. *Above* is an indicator if the family income is above the eligibility limit, and 0 otherwise. $Income$ is the reported family income divided by the income limit for full payments. For households without married couples or children under 19, the limit is $75,000. For households with married couples, the limit is $150,000. The twelve-month income is converted to the calendar year income using the adjustment factor in IPUMS and the income in 2021 is further converted to 2019 dollars using the CPI variable in IPUMS. The column headers indicate the income bandwidth used in each estimation. Control variables include household head age group and family size group indicators. Standard errors are clustered by state.

| Panel A: Homeownership | | | | |
|---|---|---|---|---|
| | [0.9,1.1] | [0.875,1.125] | [0.85,1.15] | [0.825,1.175] |
| $Income \times Above$ | $-0.124$ | $-0.289^{***}$ | $-0.140^{**}$ | $-0.162^{***}$ |
| | (0.101) | (0.079) | (0.059) | (0.040) |
| Controls | $Yes$ | $Yes$ | $Yes$ | $Yes$ |
| Year FE | $Yes$ | $Yes$ | $Yes$ | $Yes$ |
| R-squared | 0.179 | 0.178 | 0.175 | 0.176 |
| N | 91316 | 112388 | 134013 | 160898 |

| Panel B: Rooms per person | | | | |
|---|---|---|---|---|
| | [0.9,1.1] | [0.875,1.125] | [0.85,1.15] | [0.825,1.175] |
| $Income \times Above$ | $-0.765^{*}$ | $-0.532$ | $-0.459^{**}$ | $-0.413^{***}$ |
| | (0.436) | (0.334) | (0.195) | (0.154) |
| Controls | $Yes$ | $Yes$ | $Yes$ | $Yes$ |
| Year FE | $Yes$ | $Yes$ | $Yes$ | $Yes$ |
| R-squared | 0.493 | 0.495 | 0.498 | 0.496 |
| N | 91316 | 112388 | 134013 | 160898 |

$^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Table 5: Changes in LTI by income groups

The dependent variable is the ratio of mortgage amount to borrower income. *Quintile* $1-4$ are indicators for borrower income quintiles in each year. The sample includes the universe of HMDA home-purchase mortgages in 2019 and 2021. *Post* is an indicator variable for year 2021. Control variables include borrower age group and the number of applicants. Standard errors are clustered by the state in which the property is located.

| | (1) | (2) | (3) |
|---|---|---|---|
| *Quintile* 1×*post* | 0.265*** | 0.251*** | 0.416*** |
| | (0.028) | (0.027) | (0.028) |
| *Quintile* 2×*post* | 0.272*** | 0.258*** | 0.354*** |
| | (0.021) | (0.021) | (0.021) |
| *Quintile* 3×*post* | 0.209*** | 0.198*** | 0.256*** |
| | (0.012) | (0.011) | (0.020) |
| *Quintile* 4×*post* | 0.112*** | 0.104*** | 0.128*** |
| | (0.007) | (0.006) | (0.012) |
| Quintile dummies | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes |
| Controls*post | No | Yes | Yes |
| Year FE | Yes | Yes | No |
| County*year FE | No | No | Yes |
| R-squared | 0.165 | 0.165 | 0.350 |
| N | 9501567 | 9501567 | 9501548 |

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Stimulus payments and house price growth in 2020 and 2021

The dependent variable is the growth in house prices from 2019 to 2021. *Stimulus payments* is the total per-capita economic impact payments of 2020 and 2021 and the child tax credit payments of 2021. Other variables are defined in Table 1. Standard errors are clustered by state.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| $Stimulus\ payments$ | 0.046** | 0.048** | 0.048** | 0.054** | 0.049** | 0.045** | 0.044** | 0.038** | 0.058*** | 0.044** |
| | (0.022) | (0.021) | (0.023) | (0.023) | (0.020) | (0.018) | (0.019) | (0.018) | (0.021) | (0.019) |
| $\Delta Other\ transfer$ | | 0.013*** | 0.013*** | 0.010** | 0.008* | 0.009* | 0.008** | 0.008** | 0.008** | 0.007 |
| | | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) | (0.004) | (0.004) | (0.004) | (0.007) |
| $\Delta Non\ transfer$ | | 0.005*** | 0.005*** | 0.004*** | 0.004*** | 0.004*** | 0.004*** | 0.004*** | 0.004*** | 0.003*** |
| | | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| $\Delta Unemp\ rate$ | | -0.006 | -0.006 | -0.007 | -0.009 | -0.010 | -0.009 | -0.009 | -0.008 | -0.004 |
| | | (0.007) | (0.007) | (0.007) | (0.007) | (0.006) | (0.005) | (0.005) | (0.006) | (0.008) |
| $\Delta Pop$ | | 3.728*** | 3.727*** | 3.611*** | 2.592*** | 2.684*** | 2.066*** | 2.034*** | 1.885*** | 1.684*** |
| | | (0.231) | (0.238) | (0.235) | (0.333) | (0.356) | (0.308) | (0.310) | (0.304) | (0.294) |
| $Ln(Pop_{2019})$ | | -0.001 | -0.001 | -0.001 | 0.006 | 0.007 | 0.004 | 0.006 | 0.004 | 0.000 |
| | | (0.003) | (0.004) | (0.004) | (0.004) | (0.005) | (0.003) | (0.004) | (0.003) | (0.003) |
| $IPC_{2019}$ | | | -0.000 | -0.001 | -0.001 | -0.001 | -0.000 | -0.000 | -0.000 | -0.000 |
| | | | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| $Median\ Hvalue_{2019}$ | | | | 0.000** | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | -0.000 |
| | | | | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $Pop\ inflow$ | | | | | 1.040*** | 1.079*** | 0.734*** | 0.745*** | 0.645*** | 0.337 |
| | | | | | (0.267) | (0.275) | (0.242) | (0.240) | (0.231) | (0.205) |
| $Density$ | | | | | | -0.000 | | | | |
| | | | | | | (0.000) | | | | |
| $\Delta HP_{17-19}$ | | | | | | | 0.714*** | 0.712*** | 0.686*** | 0.381*** |
| | | | | | | | (0.123) | (0.124) | (0.124) | (0.142) |
| $WFH\ exposure$ | | | | | | | | -0.083 | | |
| | | | | | | | | (0.062) | | |
| $Remote\ share_{2019}$ | | | | | | | | | 0.617*** | 0.745*** |
| | | | | | | | | | (0.212) | (0.193) |
| State FE | No | No | No | No | No | No | No | No | No | Yes |
| R-squared | 0.021 | 0.547 | 0.547 | 0.553 | 0.585 | 0.612 | 0.671 | 0.673 | 0.682 | 0.810 |
| N | 382 | 382 | 382 | 382 | 382 | 358 | 382 | 382 | 382 | 377 |

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Stimulus payments, housing unit growth, and housing demand

The dependent variable is housing unit growth, house price growth, the sum of housing unit growth and house price growth, house price growth, housing unit growth, new home listing growth, and house price growth from 2019 to 2021, respectively. *Stimulus payments* is the total per-capita economic impact payments of 2020 and 2021 and the child tax credit payments of 2021. Control variables include changes in other transfer income, changes in non-transfer income, changes in unemployment rate, population growth from 2019 to 2021, and the log population in 2019.

| | ΔUnit | ΔPrice | ΔDemand | ΔListing | ΔPrice |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| *Stimulus payments* | -0.005** | 0.046** | 0.044** | 0.036* | 0.051** |
| | (0.002) | (0.021) | (0.021) | (0.021) | (0.022) |
| $\Delta Unit$ | | -0.398 | | | |
| | | (0.402) | | | |
| $\Delta Listing$ | | | | | -0.065 |
| | | | | | (0.044) |
| Controls | Yes | Yes | Yes | Yes | Yes |
| R-squared | 0.684 | 0.550 | 0.635 | 0.083 | 0.551 |
| N | 382 | 382 | 382 | 382 | 382 |

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Stimulus payments and home purchase mortgages

The dependent variable is the growth of home purchase mortgages, changes in loan-to-value ratio, changes in loan-to-income ratio, changes in mortgage denial rate, and changes in mortgage rate spread, respectively. *Stimulus payments* is the total per-capita economic impact payments of 2020 and 2021 and the child tax credit payments of 2021. Control variables include changes in other transfer income, non-transfer income, unemployment rate, population growth from 2019 to 2021, and the log population in 2019. In Panel B, the dependent variable is the ratio of mortgage amount to borrower income. *Quintile* $1-4$ are indicators for borrower income quintiles in each year. The sample includes the universe of HMDA home-purchase mortgages in 2019 and 2021. *Post* is an indicator variable for year 2021. Control variables include borrower age group and the number of applicants. Standard errors are clustered by the state in which the property is located.

| | Mortgage growth | ΔLTV | ΔLTI | ΔDenial rate | ΔRate spread |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| *Stimulus payments* | 0.110*** | 0.058 | -0.022 | 0.006*** | -0.059*** |
| | (0.032) | (0.146) | (0.024) | (0.001) | (0.014) |
| Controls | Yes | Yes | Yes | Yes | Yes |
| R-squared | 0.094 | 0.170 | 0.029 | 0.094 | 0.164 |
| N | 382 | 382 | 382 | 382 | 382 |

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

# Online Appendices

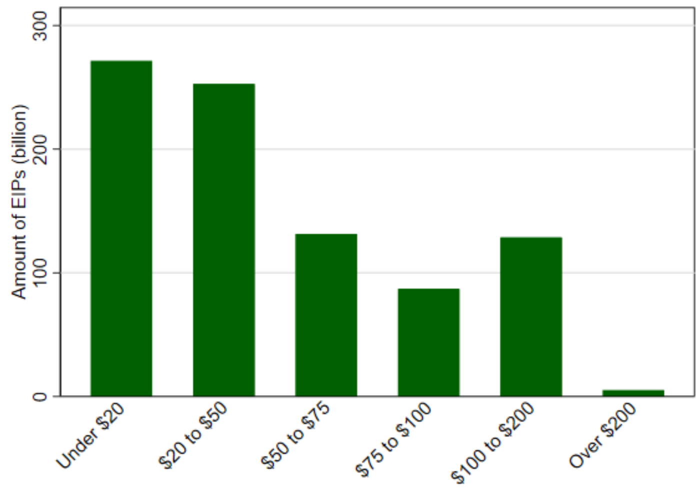



Figure A1: Amount of total EIPs and advance CTC payments by income group. This figure plots the total EIPs and advance CTC payments received by individuals with adjusted gross income below $20,000 (including those with zero or negative AGI and those who did not file a tax return in 2019 or 2020), between $20,000 and $50,000, $50,000 and $75,000, $75,000 and $100,000, $100,000 and $200,000, and over $200,000. Data source: IRS SOI Tax Stats - Coronavirus Aid, Relief, and Economic Security Act Statistics and Advance Child Tax Credit Payments in 2021.

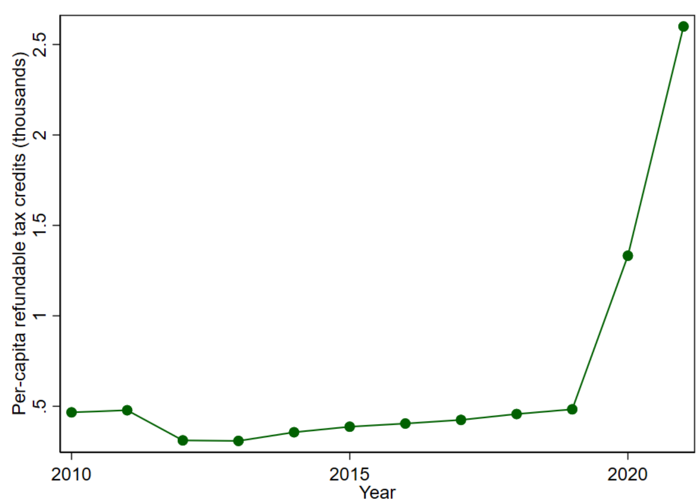



Figure A2: Per-capita refundable tax credits, 2010-2021. This figure plots the average per-capita refundable tax credits (in thousands) across MSAs in the sample from 2010 to 2021. Economic impact payments of 2020 and 2021 and the child tax credit payments of 2021 are included in this item in BEA's transfer income data by MSA.

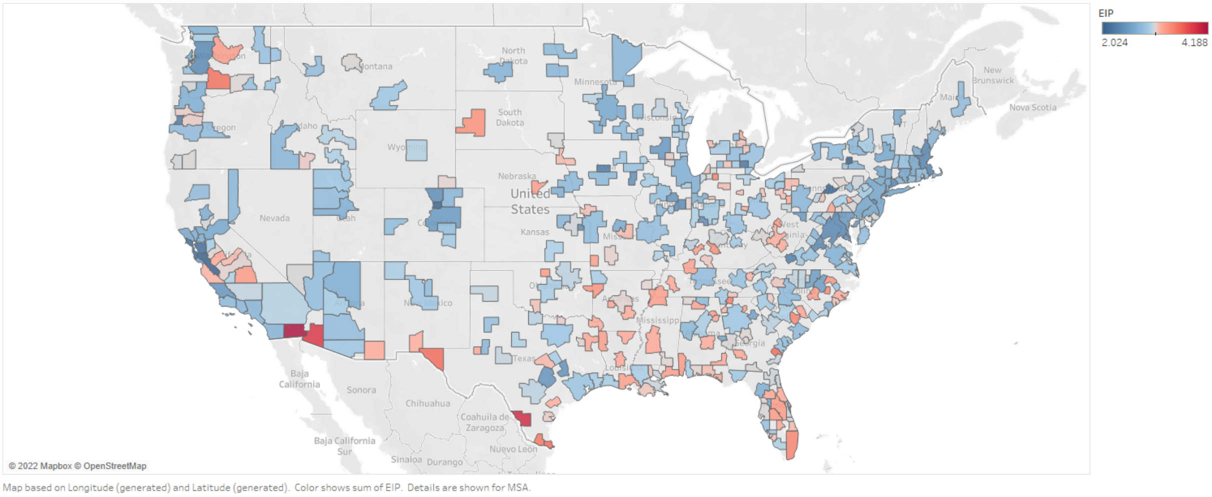



Figure A3: Per-capita stimulus payments 2020-2021. This heatmap shows the per-capita stimulus payments (in thousands dollars) across the 382 MSAs in the sample. Stimulus payments are inferred from BEA's transfer income data by MSA, as described in Section 3.1.

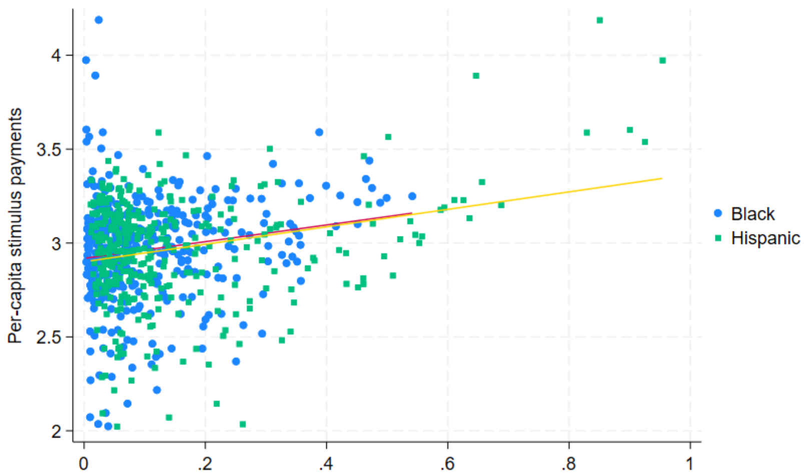



Figure A4: Stimulus payments and race and ethnicity. The figure plots the amount of per-capita stimulus payments in 2020-2021 against the fraction of MSA population that is Black and Hispanic, respectively.

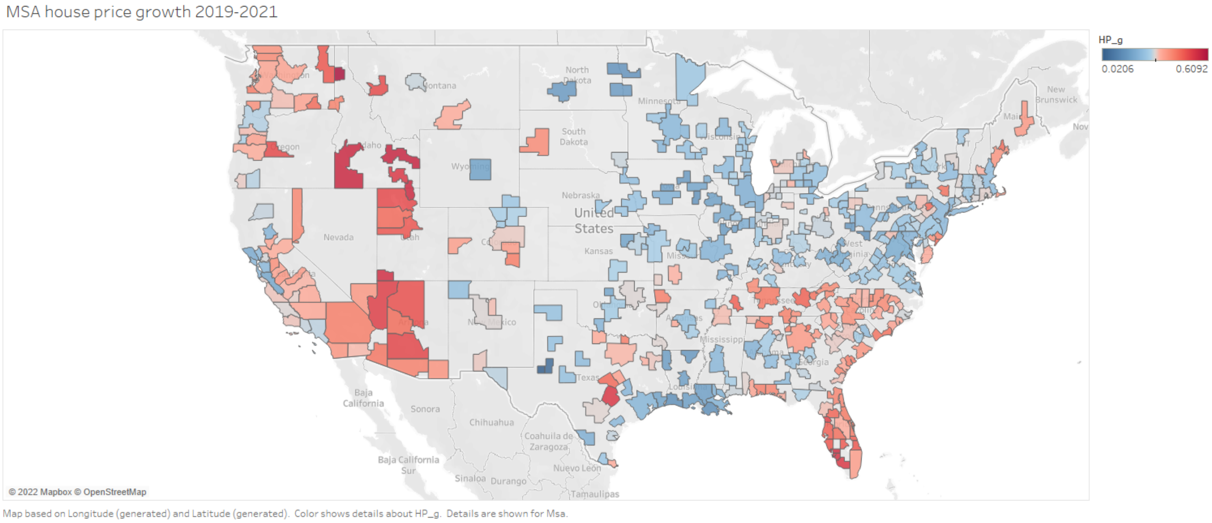



Figure A5: MSA house price growth 2019-2021. This heatmap shows the growth of house prices from 2019 to 2021 across the 382 MSAs in the sample. MSA-level house price data are from Freddie Mac.

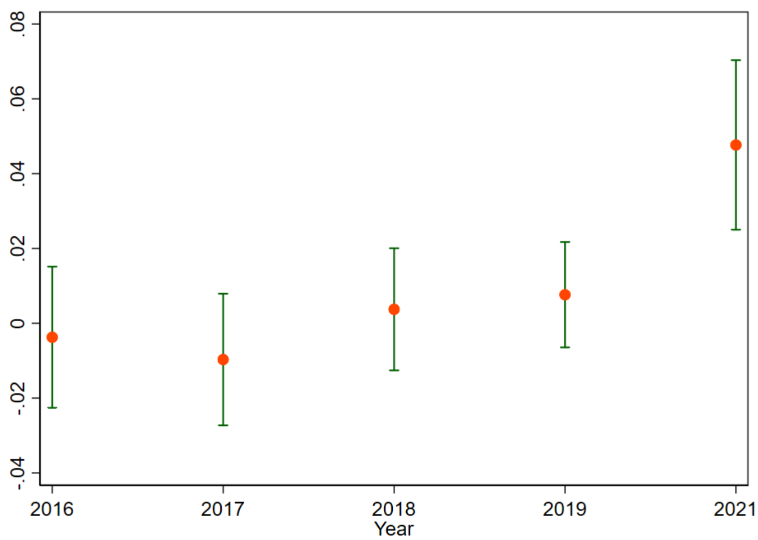



Figure A6: House price growth over a two-year period from 2016 to 2021 and stimulus payments of 2020 and 2021. House price growth during each of the five two-year periods from 2016 to 2021 (2014–2016, 2015–2017, 2016–2018, 2017–2019, 2019–2021) is regressed on the 2020–2021 stimulus payments and control variables in column (3) of Table 6. The figure plots the coefficients of *stimulus payments* and the 90% confidence intervals.

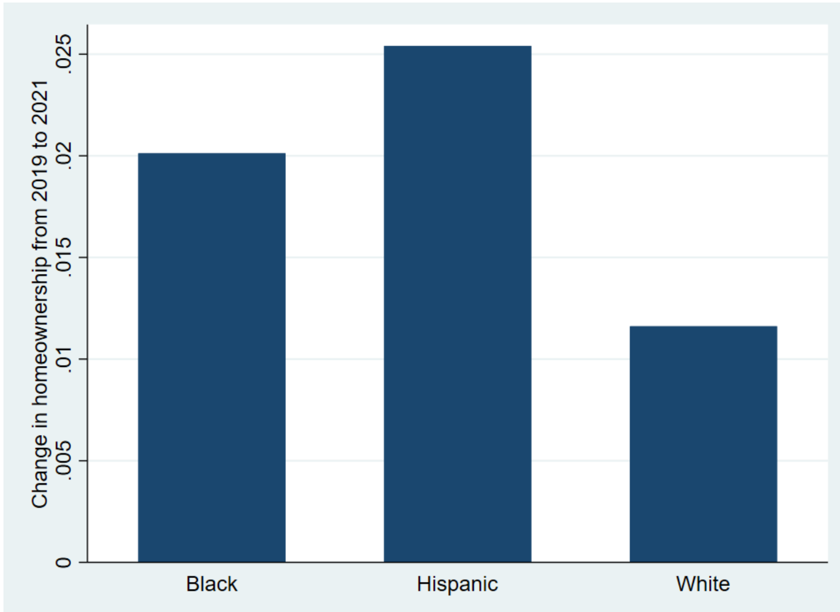



Figure A7: Changes in homeownership rate by race and ethnicity 2019-2021. Homeownership is measured as the fraction of occupied housing units that are owner-occupied. Housing units data by race and ethnicity are obtained from the one-year American Community Survey.

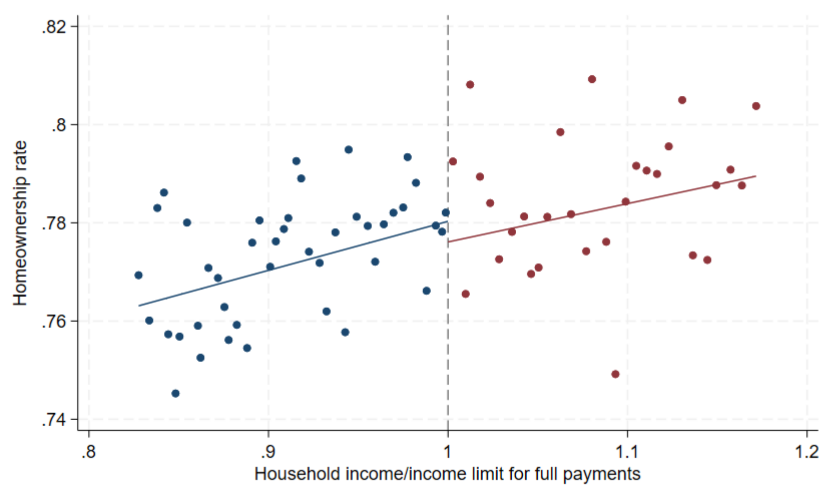



Figure A8: Household income and homeownership status in 2019. This figure presents a binned scatter plot of homeownership status and household income relative to the income limits for full stimulus payments. These income limits are $150,000 for families with a married couple and $75,000 for families without any couple or children under 19. Homeownership has been residualized from family size, age group, and married-couple indicators.

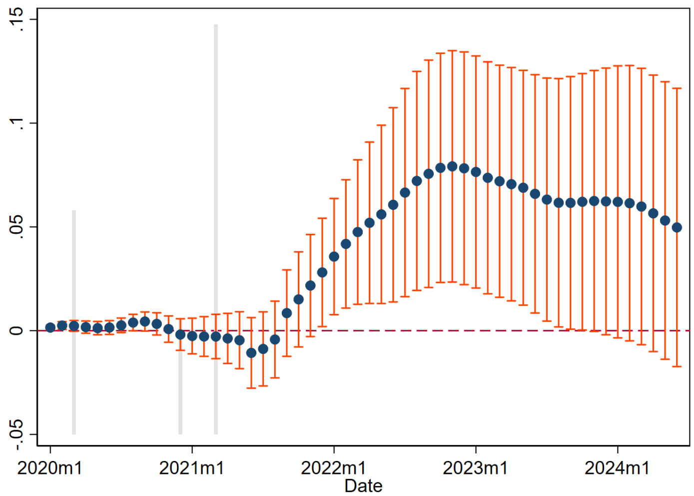


Figure A9: Evolution of house prices through 2024: Zillow Home Value Index. House price growth from December 2019 to each of the subsequent month through July 2024 is regressed on the 2020–2021 stimulus payments and all the control variables in Table 6. The figure plots the coefficient of *stimulus payments* and the 90% confidence interval from each of the regressions.

Table A1: Stimulus payments and race composition at the MSA level

The dependent variable is per-capita stimulus payments in 2020 and 2021. *Black ratio* and *Hispanic ratio* is the fraction of population in an MSA that are Black and Hispanic, respectively.

| | (1) |
|---|---|
| $Black\ ratio_{2019}$ | 0.655*** |
| | (0.129) |
| $Hispanic\ ratio_{2019}$ | 0.572*** |
| | (0.087) |
| R-squared | 0.130 |
| N | 382 |

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A2: Income and homeownership around stimulus payment income thresholds in 2019

The dependent variable is an indicator equal to 1 if the housing unit is owned, and 0 if rented. *Above* is an indicator if the family income is above the eligibility limit, and 0 otherwise. *Income* is the reported family income divided by the income limit for full payments. For households without married couples or children under 19, the limit is \$75,000. For households with married couples, the limit is \$150,000. The twelve-month income is converted to the calendar year income using the adjustment factor in IPUMS. The column headers indicate the income bandwidth used in each estimation. Control variables include household head age group and family size group indicators. Standard errors are clustered by state.

| | [0.9,1.1] | [0.875,1.125] | [0.85,1.15] | [0.825,1.175] |
|---|---|---|---|---|
| $Income \times Above$ | 0.011 | −0.037 | −0.055 | −0.007 |
| | (0.142) | (0.089) | (0.069) | (0.058) |
| Controls | *Yes* | *Yes* | *Yes* | *Yes* |
| Year FE | *Yes* | *Yes* | *Yes* | *Yes* |
| R-squared | 0.178 | 0.177 | 0.174 | 0.172 |
| N | 91680 | 116579 | 136651 | 159067 |

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A3: Stimulus payments and house price growth by MSA population

The dependent variable is the growth in house price from 2019 to 2021. *Stimulus payments* is the total per-capita economic impact payments of 2020 and 2021 and the child tax credit payments of 2021. Control variables include the total increase in per-capita transfers excluding stimulus payments and in per-capita non-transfer income from 2019 to 2020 and 2021, the growth rate of total population from 2019 to 2021, changes in unemployment rate from 2019 to 2021, and log population in 2019. Standard errors are clustered by state.

| | Large MSAs | Small MSAs | Pop-weight |
|---|---|---|---|
| | (1) | (2) | (3) |
| *Stimulus payments* | $0.045^{**}$ | $0.058^{**}$ | $0.089^{***}$ |
| | (0.018) | (0.026) | (0.030) |
| Controls | Yes | Yes | Yes |
| R-squared | 0.601 | 0.524 | 0.637 |
| N | 191 | 191 | 382 |

$^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Table A4: Economic impact payments and house price growth in 2020 and 2021

The dependent variable is the growth in house prices from 2019 to 2021. $EIPs$ is the total per-capita economic impact payments of 2020 and 2021. Other variables are defined in Table 1. Standard errors are clustered by state.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| $EIPs$ | 0.060** | 0.061** | 0.063** | 0.072*** | 0.065*** | 0.062*** | 0.059*** | 0.075*** | 0.061*** |
| | (0.028) | (0.023) | (0.024) | (0.024) | (0.020) | (0.021) | (0.020) | (0.021) | (0.021) |
| $\Delta Other\ transfer$ | | 0.012** | 0.012** | 0.009* | 0.007 | 0.007* | 0.007* | 0.007* | 0.004 |
| | | (0.005) | (0.005) | (0.005) | (0.005) | (0.004) | (0.004) | (0.004) | (0.007) |
| $\Delta Non\ transfer$ | | 0.005*** | 0.005*** | 0.004*** | 0.004*** | 0.004*** | 0.004*** | 0.004*** | 0.003*** |
| | | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| $\Delta Unemp\ rate$ | | -0.005 | -0.005 | -0.006 | -0.008 | -0.008 | -0.008 | -0.007 | -0.003 |
| | | (0.007) | (0.007) | (0.007) | (0.007) | (0.005) | (0.005) | (0.006) | (0.007) |
| $\Delta Pop$ | | 3.699*** | 3.702*** | 3.570*** | 2.582*** | 2.052*** | 2.040*** | 1.869*** | 1.667*** |
| | | (0.233) | (0.237) | (0.229) | (0.336) | (0.306) | (0.309) | (0.300) | (0.293) |
| $Ln(Pop_{2019})$ | | -0.000 | -0.000 | -0.000 | 0.006 | 0.005 | 0.005 | 0.004 | 0.001 |
| | | (0.003) | (0.004) | (0.004) | (0.004) | (0.003) | (0.004) | (0.003) | (0.003) |
| $IPC_{2019}$ | | | 0.000 | -0.000 | -0.001 | -0.000 | -0.000 | -0.000 | 0.000 |
| | | | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| $Median\ Hvalue_{2019}$ | | | | 0.000*** | 0.000 | 0.000 | 0.000 | 0.000 | -0.000 |
| | | | | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $Pop\ inflow$ | | | | | 1.013*** | 0.703*** | 0.709*** | 0.612*** | 0.324 |
| | | | | | (0.263) | (0.228) | (0.229) | (0.221) | (0.201) |
| $\Delta HP_{17-19}$ | | | | | | 0.717*** | 0.717*** | 0.691*** | 0.380*** |
| | | | | | | (0.123) | (0.124) | (0.123) | (0.138) |
| $WFH\ exposure$ | | | | | | | -0.032 | | |
| | | | | | | | (0.060) | | |
| $Remote\ share_{2019}$ | | | | | | | | 0.621*** | 0.757*** |
| | | | | | | | | (0.191) | (0.187) |
| State FE | | | | | | | | | |
| R-squared | 0.030 | 0.554 | 0.554 | 0.562 | 0.592 | 0.679 | 0.679 | 0.690 | 0.813 |
| N | 382 | 382 | 382 | 382 | 382 | 382 | 382 | 382 | 377 |

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A5: County level stimulus payments and house price growth

The dependent variable is the growth in house prices from 2019 to 2021. Column (1) includes only counties located in multi-county MSAs. *Stimulus payments* is the total per-capita economic impact payments of 2020 and 2021 and the child tax credit payments of 2021. Control variables include the total increase in per-capita transfers excluding stimulus payments and in per-capita non-transfer income from 2019 to 2020 and 2021, the growth rate of total population from 2019 to 2021, changes in unemployment rate from 2019 to 2021, log population in 2019, the inflow of population from outside of the county in 2020 and 2021 divided by population in 2019, and the fraction of population living in urbanized areas, population density, and the distance to the Central Business District of the MSA. Standard errors are clustered at the state level.

| | (1) | (2) |
|---|---|---|
| *Stimulus payments* | 0.043*** | 0.038*** |
| | (0.008) | (0.008) |
| Controls | Yes | Yes |
| MSA FE | No | Yes |
| R-squared | 0.338 | 0.826 |
| N | 932 | 932 |

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$