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US Housing Market during COVID-19: Aggregate and Distributional Evidence

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Abstract

Using zip code-level data and nonparametric estimation, I present eight stylized facts on the US housing market in the COVID-19 era. Some *aggregate* results are: (1) growth rate of median housing price during the four months (April-August 2020) since the Federal Reserve's unprecedented monetary easing has accelerated *faster* than any four-month period in the lead-up to the 2007-09 global financial crisis; (2) the increase in housing demand in response to lower mortgage interest rates displays a structural break since March 2020 (housing demand has increased by much more than before). These results indicate either the existence of "fear of missing out" or COVID-induced fundamental changes in household behavior. In terms of *distributional* evidence, I find that the increase of housing demand seems more pronounced among the two ends of the income distribution, possibly reflecting relaxed liquidity constraints at the lower end and speculative demand at the higher end. I also find that the developments in housing price, demand, and supply since April 2020 are similar across urban, suburban, and rural areas. The paper highlights some potential unintended consequences of COVID-fighting policies and calls for further studies of the driving forces of the empirical findings.

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I. Introduction

On March 3, 2020, the Fed cut the benchmark rate by 50 basis points to 1-1.25 percent; on March 15, 2020, in another bold action, the Fed cut the rate to 0-0.25 percent. On June 10, 2020, the "dot plot" indicated that the rate would be kept in the range of 0-0.25 percent through 2022 and Chairman Powell announced that the purchases of MBS would continue, triggering the 30-year fixed mortgage rate to hit a record low of 2.97%. On July 16, the rate dropped again and marked the seventh record low this year. At the same time, house prices have surged. According to the Case-Shiller National Home Price Index, real house prices rose 45 percent from February 2012 through May 2020, the latest data. Numerous news articles and anecdotal evidence suggest that the US housing market is experiencing a surprising boom. On July 31, Nobel laureate Robert Shiller remarked in *New York Times*: "*That is a remarkable record, considering that the United States is grappling with the coronavirus pandemic, a major recession and social upheaval*."

Against this backdrop, this paper presents some stylized facts on the US residential housing market during the COVID-19 crisis, using zip code-level data and nonparametric estimation. It aims to draw attention to some unintended aggregate and distributional effects of the COVID-fighting policies and serves as a first step for further studies, particularly if the preliminary evidence points to a build-up of the systemic risk. Indeed, one finding of the paper is that the year-on-year growth rate of the median price per square foot in the recent four months (April-August 2020) has accelerated *faster* than any four-month period in the lead-up to the 2007-09 global financial crisis. Moreover, this is the case across urban, suburban, and rural areas.

To understand these findings and their policy implications, it is useful to lay out the various driving forces of the housing market developments. On the one hand, COVID-19 is an unprecedented negative shock to households' incomes (both the current and the expected incomes due to massive layoffs), leading to a significant downward pressure on the housing price via the depressed demand. On the other hand, housing price can be higher during COVID-19 because of (a) higher housing demand induced by the central bank's unprecedented monetary easing, part of which is speculative housing demand ("fear of missing out") and part of which is the demand from previously liquidity-constrained low-income households (who were borrowing up to the debt-service limits before the monetary easing)[2]; (b) lower housing supply due to stay-at-home orders (and sellers' reluctance to supply the houses out of COVID infection fears).. Hence, it remains unclear *a priori* which force would dominate.

These mechanisms can result in some unintended consequences. For example, excessively high mortgage borrowing and leverage may emerge, sowing *seeds* for the next crisis similar to the subprime mortgage crisis during 2007-09. This is particularly the case if it is the households with low or volatile incomes who have leveraged up more. In addition, inequality may worsen because those who buy houses and benefit from the ultra-easy monetary and financial conditions have high/stable incomes. Indeed, the median age of US homebuyers is 47, while the median age of people working in restaurants—a person-to-person contact service industry that suffered significant COVID-induced job losses—is 29, so a relatively small number of potential near-term homebuyers lost their jobs (*Financial Times*, June 22, 2020).

The rest of the paper is structured as follows. Section II reviews related literature; Section III describes the data and methodologies; Section IV presents the results, including the aggregate evidence, distributional evidence, and results after accounting for the urban status of the zip code, the composition change in housing supply, and the behavioral change of households; Section V concludes and discusses some policy implications. The appendix collects some technical details.

II. LITERATURE REVIEW

The paper contributes to four strands of literature. First, it contributes to a small emergent literature about the housing markets during COVID-19. Ling, Wang, and Zhou (2020) study the effect of COVID-19 on the US *commercial* real estate prices and find a negative relation between the growth of COVID-19 cases and the risk-adjusted return of firms' individual commercial property holdings. The first such study on the US *residential* real estate market is done by D'Lima, Lopez, and Pradhan (2020), who find no aggregate pricing effect but find a significant decrease in listings in the shutdown and re-opening periods. On the Chinese

[2] These two forces also reinforce each other: The higher housing prices caused by the speculative housing demand (particularly from high-income households) push up the overall housing price index in the country; this induces low-income households to also expect higher future housing prices and thus accelerate their house-purchase timelines (in an attempt to avoid buying houses at higher prices in the future).

residential real estate market, Bayoumi and Zhao (2020) document that the upward trend of the housing price has not been reversed by the COVID-19 shock, and highlight the role of a "slow-moving" structural vulnerability—financial market incompleteness—using a DSGE model.

This paper also studies the US residential real estate market, and complements D'Lima, Lopez, and Pradhan (2020) along four dimensions: (a) the former focuses on the effects of Fed's monetary easing rather than the government's shutdown policies as in the latter, and attempts to shed light on the unintended effects of monetary easing during any period of time, including a pandemic (which occurs infrequently); (b) the former focuses more on housing demand by making use of a novel indicator,[3] and the latter focuses more on housing supply; (c) the former also studies the distributional effect (across different *income groups*), complementing the latter (which finds differential effects across different *property types*); and finally (d) the former uses nonparametric estimation and structural break models, and the latter uses difference-in-difference models.

Second, the paper contributes to the economic history literature about the effects of health crises on housing markets. Ambrus, Field, and Gonzalez (2020) study the impact on housing prices of a cholera epidemic in a neighborhood of 19th-century London. They find that a decade after the epidemic, housing prices were significantly lower just inside the catchment area of the water pump that transmitted the disease, and that such differences persist over the following 160 years. Francke and Korevaar (2020) study the plague in Amsterdam and cholera in Paris between the late 16th century and 1811. They find large reductions in rents and house prices within the affected areas during the first six months of an epidemic; however, both cities quickly reverted to their initial price paths. More recently, Wong (2008) finds a 1-3 percent decrease in prices for properties in Hong Kong that were directly affected by the 2003 SARS epidemic.

Third, the paper contributes to an extensive literature on the aggregate and distributional effects of monetary easing and low interest rates. For example, on *aggregate* effects, Acharya and others (2011) point out the important role of low interest rates, relaxed lending standards,

[3] Relatedly, Bolhuis and Cramer (2020) study the impact of demographic trends on housing demand in the US. Their empirical analysis finds that since the housing trough in 2012, larger homes (and those in neighborhoods with a higher share of baby boomers) underperform substantially in terms of price growth, home sales, and liquidity. In the next two decades, as more and more baby boomers look to downsize, more than a quarter of the US homes occupied by their owners will likely hit the market (Romem, 2019).

and government guarantees in the US mortgage market in driving the 2007-09 housing crisis.[4] McDonald and Stokes (2013) find that the Fed's low interest rate policy during 2001–04 was a cause of the subsequent housing price bubble, by applying Granger causality analysis to a panel dataset for 20 US cities during 1987-2010. By contrast, Merrouche and Nier (2010) (using cross-country analysis) and Dokko and others (2011) (using a common statistical approach) find that this is not the case and point to other factors such as inadequate regulation and excessive credit provision.

On *distributional* effects, Domanski, Scatigna, and Zabai (2016) find that changes in wealth inequality in five European countries and the US since 2009 are driven by movements in equity and house prices (which are in turn driven by monetary easing). Moreover, they find that house price increases alone tend to reduce wealth inequality, and equity price increases tend to increase it. Using a DSGE model of the euro area, Hohberger, Priftis, and Vogel (2020) find that expansionary conventional policy and QE shocks tend to mitigate income and wealth inequalities. And with a larger sample (a panel of 32 advanced and emerging market countries over the period 1990–2013), Furceri, Loungani, and Zdzienicka (2018) find that contractionary monetary policy shocks on average raise income inequality, and that the effect is asymmetric (policy tightening raises inequality more than easing reduces it) and depends on the state of the business cycle.

Finally, the paper contributes to a growing literature about the general economic effects of COVID-19 and government policies. Regarding *short-term aggregate* effects, Deb and others (2020) find that containment measures are associated with a very large decline of economic activity, amounting to a loss of about 15 percent in industrial production over a 30-day period; Chen and others (2020) find that deterioration of economic conditions preceded the introduction of non-pharmaceutical interventions (NPIs, such as social distancing) and a gradual recovery started before formal reopening. Regarding *medium-term aggregate* economic effects, Correia, Luck, and Verner (2020) analyze monthly data across US cities during the 1918 Flu Pandemic,

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[4] Relatedly, several studies examine the excessive risk-taking induced by the US government's mortgage guarantee. Keys and others (2010), and Keys, Seru, and Vig (2012) study the *extensive* margin, that is, banks relax the lending criteria and extend mortgage loans to risky borrowers. Zhao (2019) and Zhao (2020) study the *intensive* margin, that is, banks raise the mortgage interest rate and/or the leverage ratio of the same borrower (for the same borrower, a higher interest rate and/or a higher leverage ratio means a larger repayment burden, and thus, a higher default risk).

and find that NPIs are associated with better economic outcomes in the medium term.[5] Regarding the *distributional* effects and the designs of the COVID-related government policies, Glover and others (2020) study optimal mitigation and redistribution policies, and find that the young who work in the sector partially shuttered would lose the most, especially when it is costly to soften the distributional consequences via public transfers; Furceri and others (2020) find that major epidemics in the last two decades have led to increases in multiple measures of inequality in affected countries, despite being much smaller in scale than COVID-19; Bronka, Collado, and Richiardi (2020) find that the UK's COVID rescue package would have a progressive effect and reduce poverty rate by 1.1 percentage points; Gerardi, Loewenstein, and Willen (2020) analyze the effects of a streamlined refinance program that allows borrowers to refinance without providing employment or income documents; Goodman and Magder (2020) discuss the renter direct payment program that aims at assisting renters who are disproportionally affected by the pandemic.[6]

III. Data, Summary Statistics, and Methodologies

A. Data Description

Since housing data in most countries are inadequate and infrequent, this study uses data from the US. But the results can shed light on other countries as well. Specifically, the housing data are from the zip code-level monthly panel databases released in the realtor.com library, covering most zip codes in the US from July 2017 to August 2020. Two databases are used, including the "realtor.com residential listings database" for median listing price per square foot, etc., and the "realtor.com market hotness index" for housing demand.[7] In particular, the housing demand (or

[5] Barro, Ursua and Weng (2020) also quantify the medium-to-long-term effects by analyzing annual data for 48 countries. They find that the 1918 Flu Pandemic lowered real GDP by 6-8% in the typical country, which is suggested to be the upper bound of the effects of COVID-19. Aum, Lee, and Shin (2020) study both short-term and medium-term effects, and find that a longer lockdown eventually mitigates the GDP loss as well as flattens the infection curve.

[6] Other studies on inequality and distributional effects include Chetty and others (2020), Schmitt-Grohé, Teoh, and Uribe (2020), Palomino, Rodríguez, and Sebastian (2020), and Galletta and Giommoni (2020). Some other studies on government's COVID interventions analyze the corporate credit channel, such as Acharya and Strafen (2020), Elenev, Landvoigt, and Van Nieuwerburgh (2020), and Greenwald, Krainer, and Paul (2020).

[7] No data on property types (single-family, condo, etc.) are available. However, since the study uses the *median* growth rates (across all zip codes) of the *median* price per square foot (across all properties in a given zip code), the lack of information on property types does not seem to be a major concern. The data and detailed descriptions for the data are available at https://www.realtor.com/research/data/. The

"hotness") used in the paper is the "demand score", measured as the online views per property, which is a credible and useful way to disentangle demand from the many other drivers of the housing price.

These data are merged with some other sources: first, the monthly mortgage rate data from the Primary Mortgage Market Survey, a frequently-used source provided by Freddie Mac— to be more representative, I use the rate for conventional, confirming 30-year fixed-rate mortgages, given that this is the most common product type in the US; second, the daily (national) data on effective federal funds rate (EFFR) from New York Fed, averaged to a monthly frequency; third, the latest American Community Survey (ACS)'s zip code-level median income (cross-sectional) data, which are the 2014-18 5-year estimates. According to the US Census Bureau, the 5-year estimates from the ACS are "period" estimates that represent data collected over a period of time, and "the primary advantage of using multiyear estimates is the increased statistical reliability of the data for less populated areas and small population subgroups."[8] These 5-year estimates are available for all geographical areas down to the block-group level. In total, over 578,000 geographical areas are covered. Chetty and others (2020) also use such data to track the economic activities during COVID-19 in their paper and real-time economic tracker.[9]

B. Summary Statistics

Table 1 summarizes the merged raw data for the key indicators. As expected, outliers exist for all the major housing indicators. For example, the (median) year-on-year growth rate of the (median) views per property (a measure of housing demand) can be as high as 4,248 percent, and even more extreme outliers exist for the growth rate of the median price per square foot.

The following steps are conducted to remove the outliers. First, I remove observations with a 500 percent or higher growth rate of property views. There are 102 such observations, but they are *disproportionally* distributed in June 2020 (10 percent), July (16 percent), and August (28 percent, left panel of Figure 1). Moreover, this is also the case for the 4,242 observations with a 200-500 percent growth rate of property views (right panel of Figure 1): June 2020

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residential listings database is also available at a weekly frequency, but the weekly data are at the national/metro levels only and have fewer indicators. Moreover, the hotness index data are only available at a monthly frequency. Hence, this study uses monthly data for both databases.

[8] See https://www.census.gov/data/developers/data-sets/acs-5year.html.

[9] See https://tracktherecovery.org/.

accounts for 10 percent, July 2020 26 percent, and August 2020 46 percent. Since the scope of the paper is to analyze the *unusual* market behavior since March 2020, I keep all the observations whose growth rates of property views are below 500 percent.

Second, to be consistent with the treatment for demand, I remove observations with a 500 percent or higher growth rate of active listings, a measure of housing supply. 131 such observations are removed.

Third, for the key housing price variable (growth rate of median price per sqft), the 126 observations with a 500 or higher growth rate are distributed relatively evenly across months (left panel of Figure 2), so are the 412 observations with a 200-500 growth rate (right panel of Figure 2). Therefore, I drop these observations to obtain a dataset with more moderate price growth rates (without causing an obvious sample selection bias).

Table 1. Summary Statistics before Cleaning

Variable	Unit	N	Mean	Min	Median	Max	SD
zip	NA	525,606	NA	1,001	NA	99,925	NA
Month	NA	525,606	NA	201707	NA	202008	NA
PropertyViews_yy	percent	525,605	26	-96	18	4,248	47
Listing_yy	percent	467,583	-3	-87	-8	6,800	44
MedianP_sqft_yy	percent	490,215	77	-100	5	30e+6	42,783
MedianPrice_sqft	$	525,606	160	0	128	2,452	147
Median_sqft	NA	525,606	1,837	0	1,824	9,012	744
Median_sqft_yy	percent	490,215	2	-100	0	463,100	683
30Yr Fixed Mtg Rate	percent	525,606	4	3	4	5	1
MedianFamilyIncome	thousand $	523,200	79	10	71	249	32

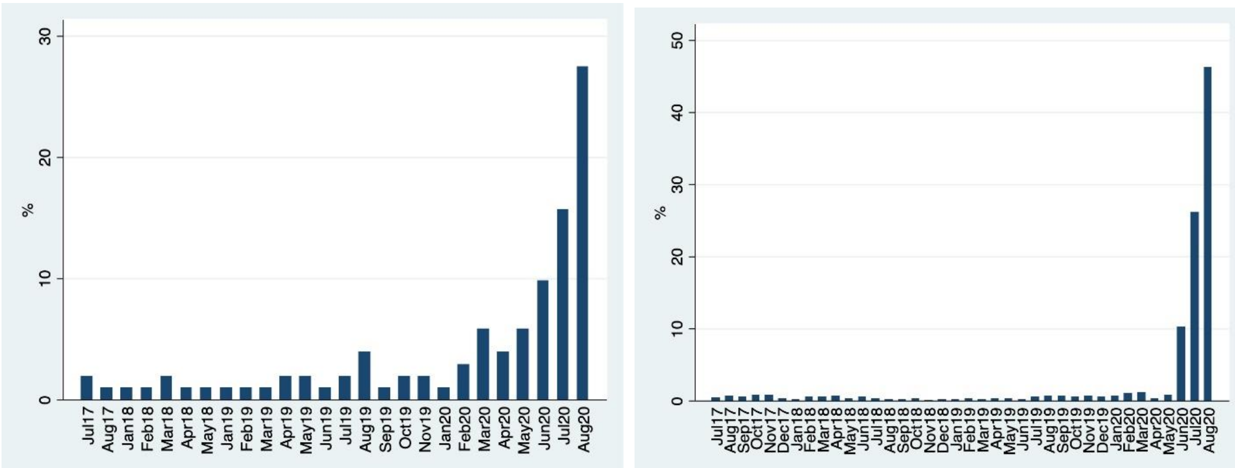
Source: realtor.com; Freddie Mac; New York Fed; American Community Survey; Author's calculations.

Table 2. Summary Statistics after Cleaning

Variable	Unit	N	Mean	Min	Median	Max	SD
zip	NA	493,956	NA	1,001	NA	99,925	NA
Month	NA	493,956	NA	201707	NA	202008	NA
PropertyViews_yy	percent	493,956	26	-96	18	500	45
Listing_yy	percent	439,143	-4	-85	-8	500	30
MedianP_sqft_yy	percent	485,186	6	-98	5	200	15
MedianPrice_sqft	$	493,956	170	0	133	2,452	146
Median_sqft	NA	493,956	1,952	0	1,862	9,012	604
Median_sqft_yy	percent	485,186	2	-100	0	494.7	16
30Yr Fixed Mtg Rate	percent	493,956	4	3	4	5	1
MedianFamilyIncome	thousand $	491,766	78	10	71	249	31

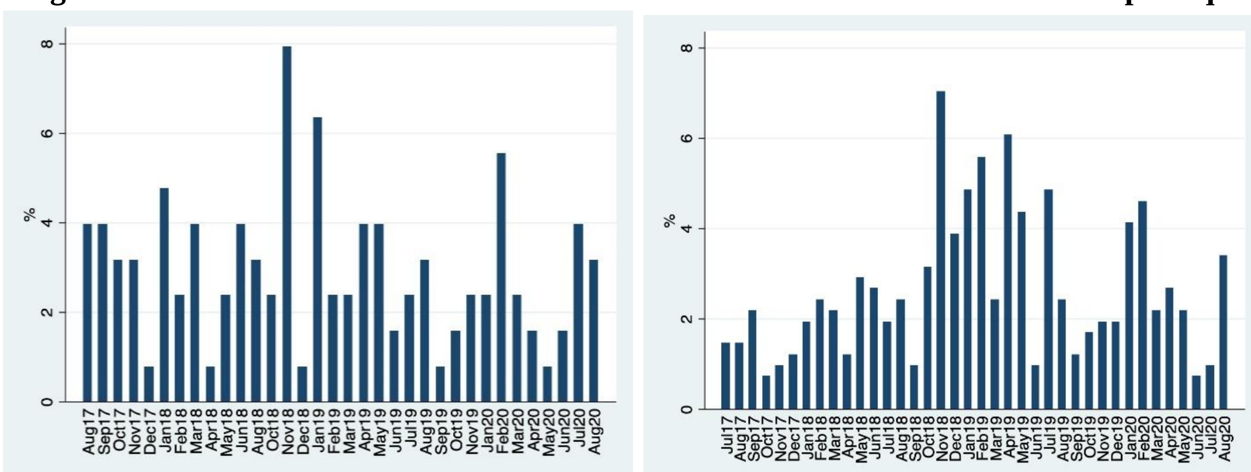
Source: realtor.com; Freddie Mac; New York Fed; American Community Survey; Author's calculations.

Figure 1. Distribution of Outliers across Months: Growth Rates of Property Views



Source: realtor.com; Author's calculations.

Figure 2. Distribution of Outliers across Months: Growth Rates of Median Price per Sqft



Source: realtor.com; Author's calculations.

Fourth, I drop the 12 observations with a 500 percent or higher grow rate of median square foot (evenly distributed across months), and some other obvious invalid observations, such as observations with 0 median price per sqft. The summary statistics after the cleaning are provided in Table 2. Note that I intentionally keep a relatively broad range for the median price per sqft and the median sqft variables; given that the analysis only involves the growth rates of these variables instead of their levels, doing so will unlikely bias the analysis and will make the analysis more comprehensive. The observations in the final sample are evenly distributed across different months (Appendix Table 1), which eliminates the sample selection bias towards any particular month.

C. Methodologies

The paper uses a variety of approaches, including:

a. Descriptive analysis.

b. Zip code-level panel regressions. Importantly, the standard errors in all regressions are *clustered* at the month level. This is because the main right-hand-side variable (interest rate) only has time variation and no cross-sectional variation, which may cause correlation across zip codes and may artificially decrease standard errors. The clustering is done by implementing the widely-used estimator by Correia (2016), which augments the fixed-point iteration of Guimaraes and Portugal (2010).[10] For the same reason, I do not use the random-effect models, and only use the fixed-effect and pooled regressions.

c. Structural break models (with the Chow test) to see whether the pandemic and the unprecedented monetary easing in March 2020 triggered a structural break in housing demand.

d. The Nadaraya-Watson kernel nonparametric model to estimate the distributional effects. This class of models has the advantage of being model-free ("*let the data speak*") and is useful to discover the patterns in a flexible way.

e. With the zip code-level data, we can control for the composition change (hence quality change) of houses available in the market. This would allow us to separate the effects of supply disruptions and to improve the identification of the effects of interest rate on housing demand.

IV. Results

This section presents the results, including five stylized facts on aggregate evidence, two facts on distributional evidence, and one fact after accounting for urban status. The results after accounting for the potential changes in the composition of houses and buyers' behavioral changes are also presented.

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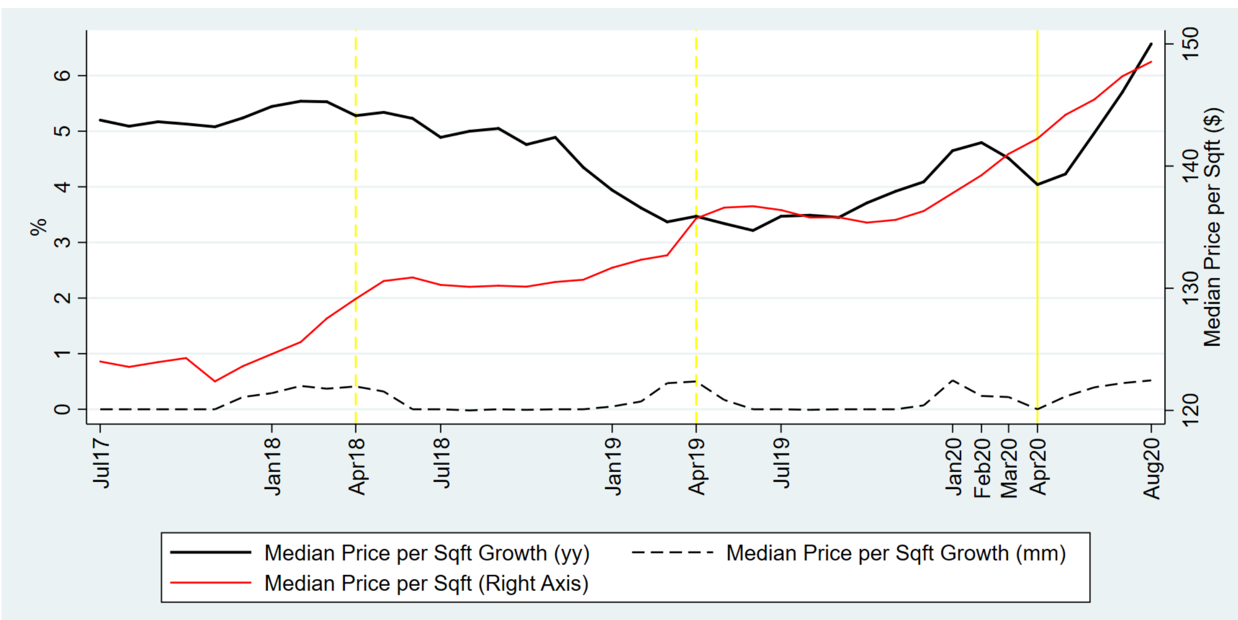
[10] The implementation is done by the reghdfe Stata package that runs linear and instrumental-variable regressions with many levels of fixed effects. More details can be found at http://scorreia.com/software/reghdfe/.

A. Aggregate Evidence

Fact #1: After a temporary slow-down in March and April 2020, the median growth rate of the median housing price bounded back quickly and *exceeded* the growth rate before the COVID-19 crisis. As shown in Figure 3, the median growth rates (both year-on-year and month-on-month) of the median price per sqft temporarily slowed down in March 2020 (the yellow vertical solid line) and April 2020, but still remained positive. They then bounced back despite the worsening of the COVID crisis in the US: the year-on-year growth rates (the black solid line) accelerated to levels higher than that before the crisis (5.0 in June 2020, 5.7 in July, and 6.6 in August, all higher than the 4.8 in February 2020); and the month-on-month growth rates (the black dash line) after April 2020 have accelerated, even though they *decelerated* or remained flat after the same month in both 2018 and 2019 (the two yellow vertical dash lines). Some zip codes experienced a year-on-year growth of more than 30 percent in each month since March 2020.

Figure 3. Median Housing Price: July 2017 – August 2020



Source: realtor.com; Author's calculations.

Fact #2: The year-on-year growth rates of the median price per sqft in the recent four months (April-August 2020) have accelerated *faster* than any four-month period in the lead-up to the 2007-09 global financial crisis (GFC). As shown in the upper panel of Figure 4, the fastest four-month acceleration of the year-on-year growth rates of house prices in the lead-up to the GFC occurred from February 2004 to June 2004, when the year-on-year growth rates accelerated by 1.8 percentage points, from 8.1 percent year-on-year to 9.9 percent. However, the acceleration during the four-month period after the Fed's unprecedented COVID responses has been even faster (even though the growth rates themselves are lower during COVID than the pre-GFC): the year-on-year growth rates accelerated by 2.6 percentage points, from 4.0 percent in April 2020 to 6.6 percent in August 2020 (lower panel of Figure 4).

Another interesting observation is that after the significant interest rate cut in November 2002 (to 1.33 percent, from 1.76 percent in October 2002), it took about eight months for the house price growth rate to enter the steady acceleration phase, starting from July 2003. By contrast, after the interest rate cut in March 2020, it only took one month to enter the acceleration phase in April 2020. Given the rapidly deteriorating COVID outbreak at the same time, this phenomenon is worth exploring further.[11]

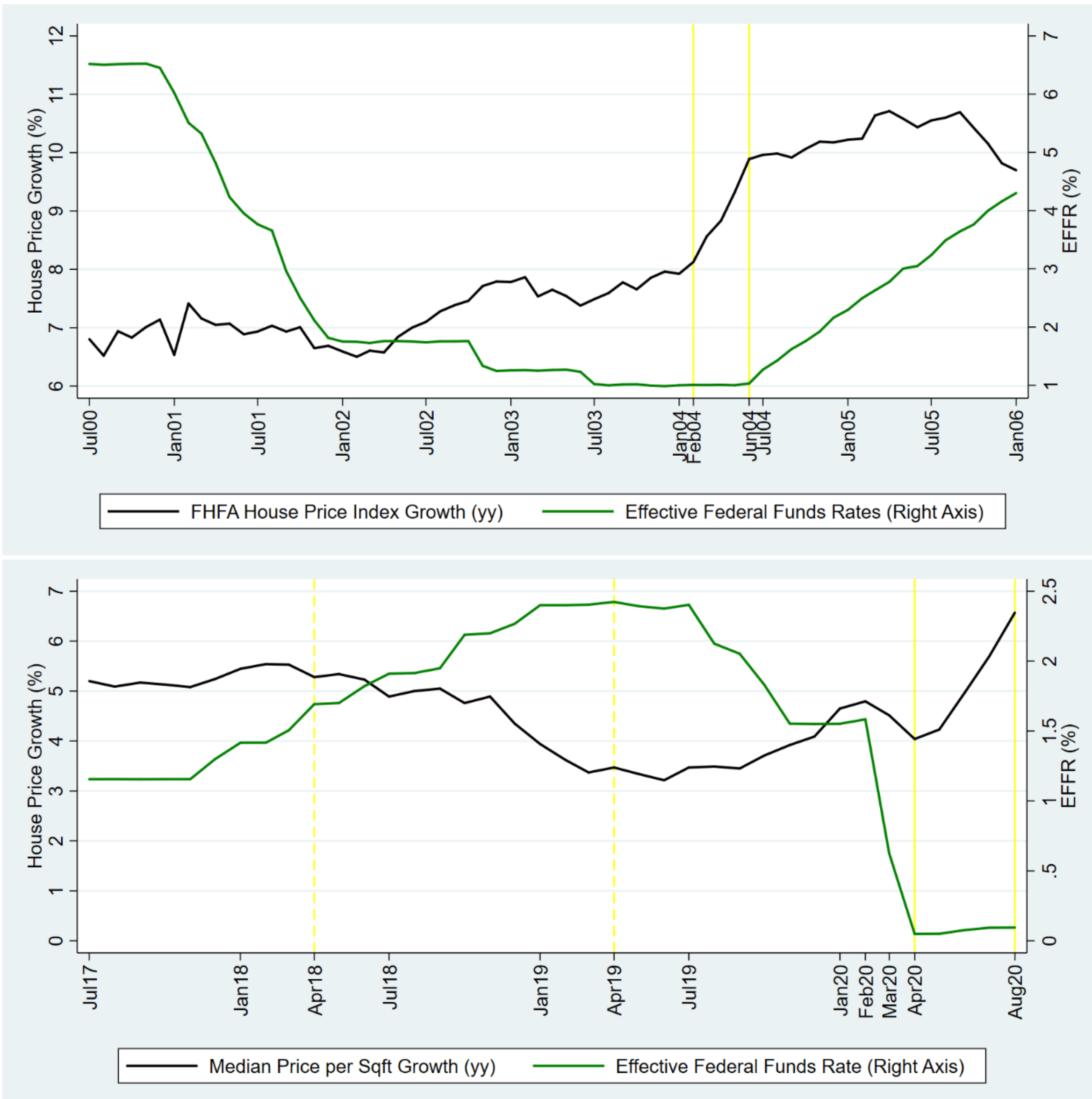
Fact #3: The decreasing trend of the housing supply since mid-2019 is amplified by COVID-19. As Figure 5 shows, the median year-on-year growth rate of the active listing (the solid purple line) has been negative since July 2019. Moreover, it has been dropping sharply since March 2020 due to the lockdown measures and possibly fears over the COVID-19 infections (sellers may be less willing to let buyers enter and view their houses). The month-on-month growth rates after April 2020 have become more and more negative, even though March-June in both 2018 and 2019 was a typical time when the month-on-month growth rates accelerated. This fact may have contributed to the rapid housing price growth since April 2020.

Fact #4: The hotness of housing demand, proxied by the online views per property, has been rising at an extraordinary rate since April 2020. As Figure 6 shows, the median views per property in a typical zip code rose by 99 percent in July 2020 and 121 percent in August 2020 (year-on-year), both of which are record highs since the data began in July 2017. The month-on-month growth rates during March-June 2020 have accelerated, even though they

[1111] Due to data constraints, the pre-GFC data are FHFA's house price index constructed from sales prices for the entire properties, as opposed to realtor.com's data on listing prices per sqft for the COVID period. Since the paper examines the year-on-year changes for both cases, this difference seems unlikely to bias the analysis.

decelerated during March-June in both 2018 and 2019 (the two yellow vertical dash lines).[12] [13] This fact may be another key contributor to the rapid housing price growth since April 2020.

Figure 4. Housing Price Growth: Comparison between GFC and COVID

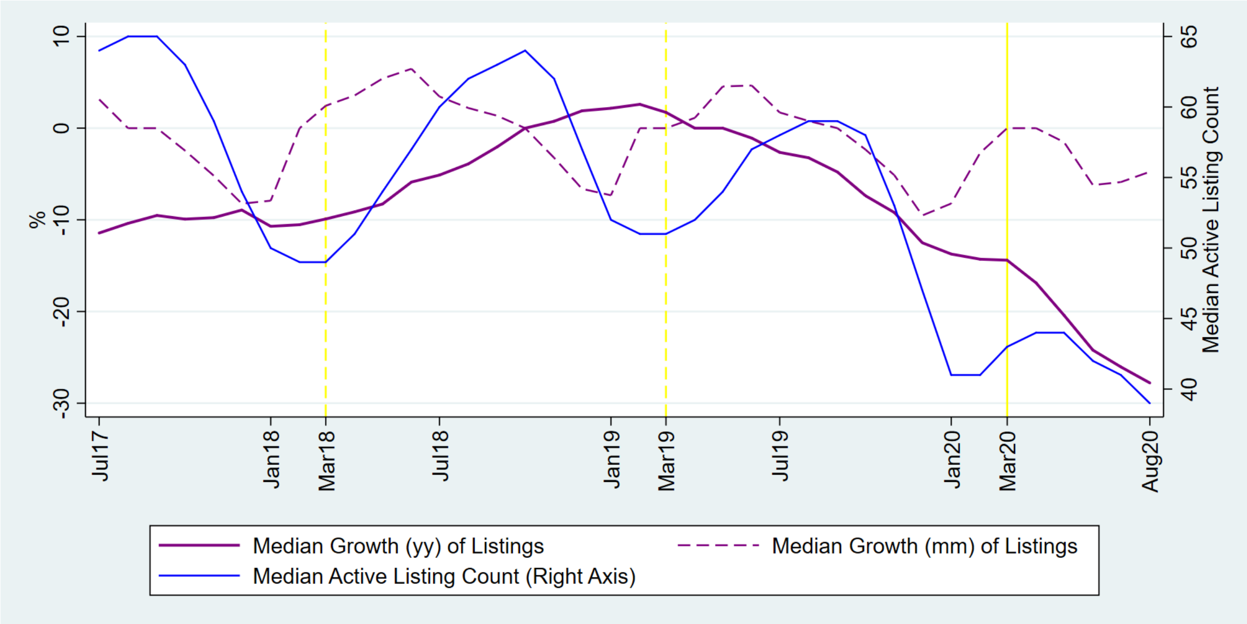


Source: FHFA; realtor.com; New York Fed; Author's calculations.

[12] The deceleration of the month-on-month growth rates during July-August 2020 is most likely due to seasonality because the same pattern was also observed in the same months of 2018 and 2019.

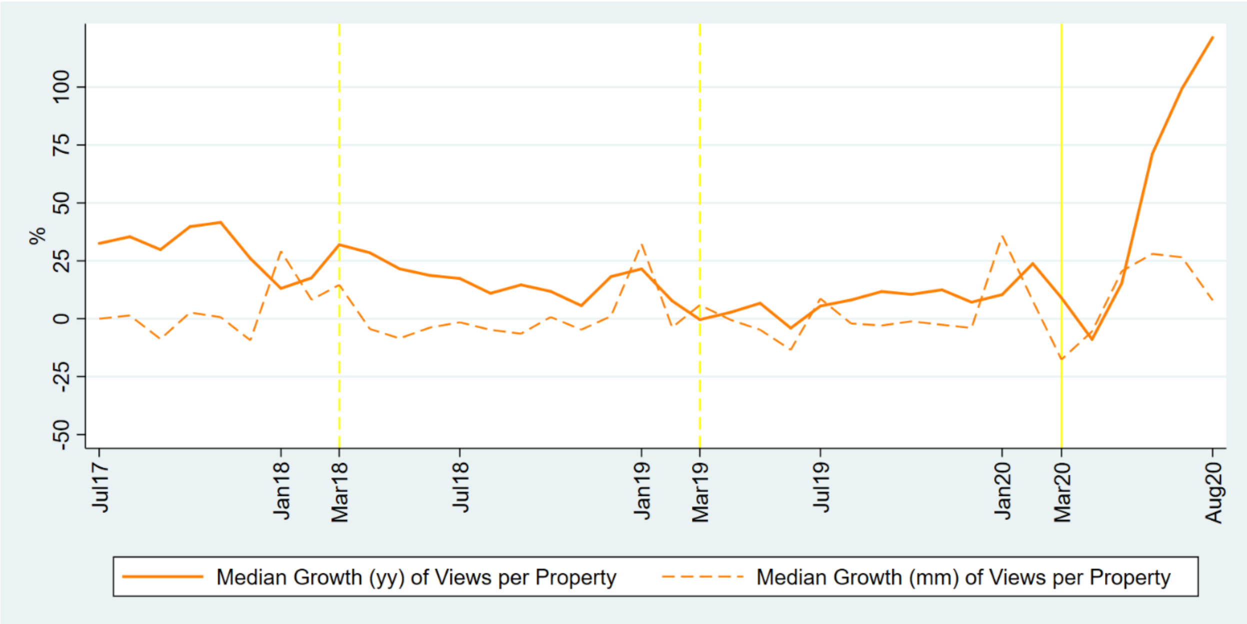
[13] Note that all the growth rates shown in the figures are the median growth across all zip codes, so they are not affected by the inclusion of observations with relatively high growth rates.

Figure 5. Housing Supply/Listings: July 2017 – August 2020



Source: realtor.com; Author's calculations.

Figure 6. Hotness of Housing Demand: July 2017 – August 2020



Source: realtor.com; Author's calculations.

Fact #5: The response of housing demand to mortgage rate displays a structural break, which is robust to falsification tests. Table 3 reports the results of zip code-level panel regressions, where the dependent variable is the (median) year-on-year growth rates of online views per property (a measure of housing demand) and the independent variable is the mortgage rate. The mortgage rate rather than EFFR is used because the pass-through from EFFR to mortgage rate may be incomplete. In addition, mortgage rate can also reflect the Fed's *non-*interest rate easing, such as via MBS purchases and other quantitative easing measures, making it more suitable for studying the impact of the monetary easing comprehensively. As discussed earlier, since the interest rate variation comes from the time dimension, only fixed-effect and pooled regressions are reported; and all standard errors are clustered at the month level to account for the potential correlations among zip codes within the same month.

As shown in Table 3, across both the fixed-effect and pooled regressions, housing demand responds much more strongly to mortgage rate since March 2020, the month when the pandemic accelerated and when the Fed easing took place. From July 2017 to February 2020, the 30-year fixed mortgage rate variable is negatively associated with the year-on-year growth of online views per property (a measure of housing demand), but the effect is statistically insignificant, also suggesting that some other factors are omitted from this simple model. However, from March 2020 onwards, the coefficient of mortgage rate is both statistically and economically significant: as the 30-year fixed mortgage rate drops by 1 percentage point, the associated year-on-year growth of online views per property increases by about 267 percentage points. The Chow test is also strongly against the null hypothesis that there is no structural break.[14] As Table 4 shows, this pattern is not observed in the falsification tests that use March 2019 as the breakpoint. In particular, such tests rule out the possibility that the pattern is driven by seasonality.[15]

These results may appear extreme, but they are obtained after dropping some outliers of the housing demand measure and may be justifiable given that many other potential factors are not explicitly controlled for. Specifically, either or both of the following two scenarios are consistent with this Fact #5:

[14] Details of the Chow tests for the structural break models and the falsification tests, including the residual sums of squares and p-values, are available upon request.

[15] Note that it is complicated to compare the housing demand responses to interest rate estimated here with those in the literature because the latter uses housing value (or size) instead of online views to measure housing demand. One apparent challenge with that approach is that the observed housing value is an equilibrium object, which also reflects supply-side factors rather than "cleanly" measuring the underlying housing demand.

Scenario (a): Fear of Missing Out (FOMO). This suggests that potential homebuyers may indeed have responded more than usual to the historically low mortgage rate, possibly out of the fear that they may miss the golden opportunity of the ultra-low interest rate and the readily available financing on the market, as well as the fear that the housing price may go even higher if they wait any longer.

Scenario (b): Other COVID-induced fundamental changes in household behavior. These include more frequent online views due to the stay-at-home orders (to be discussed below)[16]; a preference shift that assigns a higher value to owning homes (as opposed to renting) or owning larger homes due to the expectation of, say, longer work-from-home arrangements; and a higher saving propensity due to depressed spending on non-housing consumption goods.

Relatedly, there are two sets of omitted variables from the simple regressions in Table 3. The first set includes local-level COVID case growth rates, unemployment rates, and measures of economic disruptions caused by COVID. Since these variables decrease housing demand and are high when interest rates are low (the Fed cut rates against the backdrop of high COVID cases and rising unemployment rates), controlling for them would require an even stronger response to interest rate and thus would reinforce the interest rate coefficients reported here. The second set of omitted variables includes subjective valuation of owning a house, saving rate, etc. Since these variables increase housing demand and also tend to be high in a low-interest rate environment, controlling for them would weaken the reported coefficients. Hence, the direction of the omitted variable bias is unclear.

Table 3. Panel Regressions for the Full Sample

	(1) Views-YY FE All	(2) Views-YY FE Until Feb	(3) Views-YY FE Since March	(4) Views-YY Pool All	(5) Views-YY Pool Until Feb	(6) Views-YY Pool Since March
FRM_30Yr	-22.927*	-1.007	-266.940***	-22.235*	-0.703	-264.443***
	(0.056)	(0.807)	(0.006)	(0.059)	(0.863)	(0.004)
Constant	117.286**	24.589	907.639***	114.530**	23.333	899.790***
	(0.023)	(0.177)	(0.004)	(0.024)	(0.194)	(0.003)
Observations	493,917	418,589	75,044	493,956	418,618	75,338

[16] This is also a form of a preference shift, which is a shift from in-person searching to online searching.

R-squared	0.201	0.220	0.701	0.062	0.000	0.387

Note: The dependent variable is the median year-on-year growth rates of hotness of housing demand; FRM_30Yr = 30-year fixed-rate mortgage; Standard errors are clustered at the month level, and *robust* p-values are in parentheses.
Source: Author's calculations.

Table 4. Falsification Tests: Panel Regressions for the Full Sample

	(1) Views-YY FE Until August 2019	(2) Views-YY FE Until Feb 2019	(3) Views-YY FE March-August 2019	(4) Views-YY Pool Until August 2019	(5) Views-YY Pool Until Feb 2019	(6) Views-YY Pool March-August 2019
FRM_30Yr	-5.199	-22.983***	-5.765	-5.052	-22.901***	-5.448
	(0.468)	(0.000)	(0.462)	(0.476)	(0.000)	(0.438)
Constant	43.482	125.605***	29.506	42.856	125.251***	28.299
	(0.181)	(0.000)	(0.365)	(0.182)	(0.000)	(0.336)
Observations	337,360	258,390	78,764	337,402	258,433	78,969
R-squared	0.267	0.372	0.621	0.003	0.045	0.002

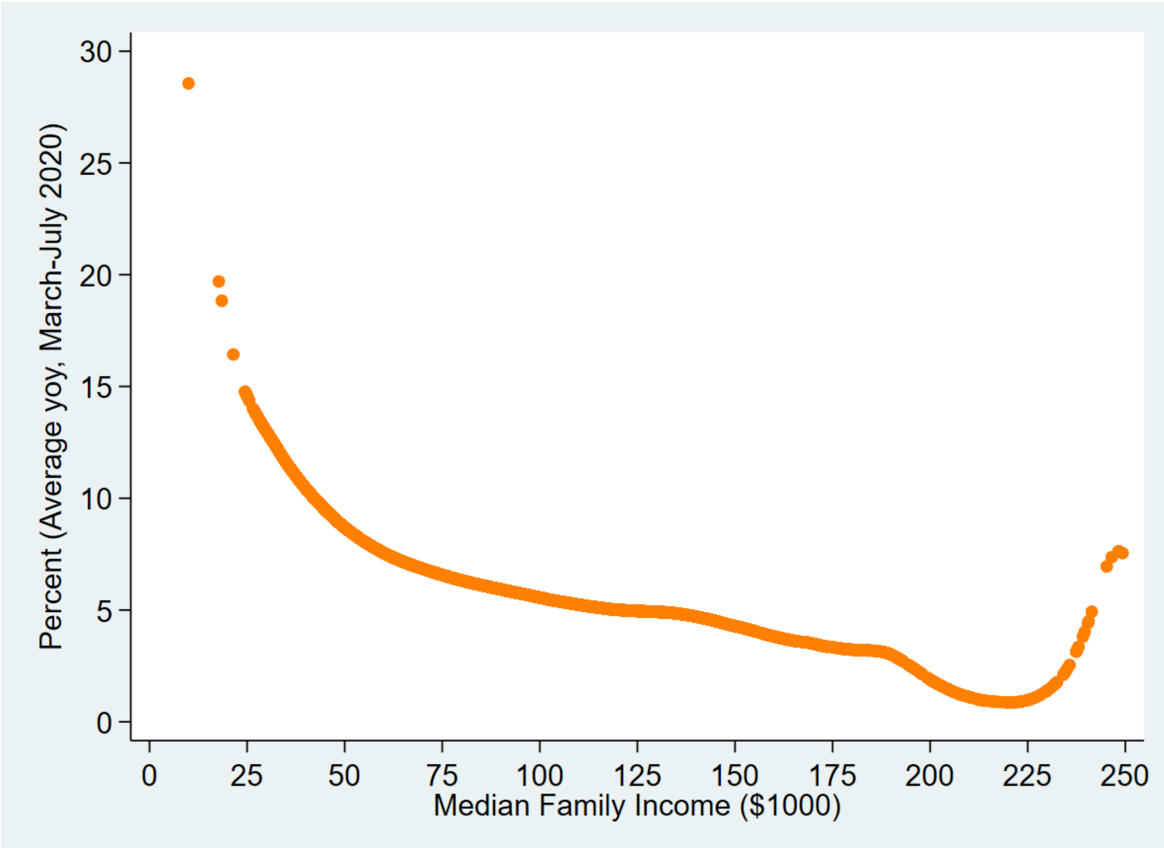
Note: The dependent variable is the median year-on-year growth rates of hotness of housing demand; FRM_30Yr = 30-year fixed-rate mortgage; Standard errors are clustered at the month level, and *robust* p-values are in parentheses.
Source: Author's calculations.

B. Distributional Evidence

This subsection turns to distributional evidence and presents two stylized facts regarding the different responses across different income groups.

Fact #6: The increase in the housing price is particularly strong at the lower-to-middle end of the zip code-level income distribution. This pattern is shown in Figure 7, which plots the nonparametric estimates of the median growth rate (year-on-year) of the median price per sqft as a function of the median family income, during March-August 2020. Even if we disregard the segment for the extremely low income group (arguably driven by noise in the data), the year-on-year house price growth rate still decreases as we move up along the income distribution, from about 15 percent in zip codes with a median family income of $25,000 to close to 0 percent in zip codes with $225,000. It then increases again for the very rich zip codes, consistent with the subsequent fact. It is worth noting that this does not necessarily mean the overall income inequality in the US is lower, because even within the low-income neighborhoods, it is the homeowners (who are relatively well-off and have stable incomes) who will likely benefit more from the low interest rates that also push up house prices.

Figure 7. Price per Sqft Growth vs Median Family Income: Nonparametric Estimation



Source: realtor.com; American Community Survey; Author's calculations.

Note that to mitigate the impact of time-specific factors and consistent with the paper's focus on the post-Fed action period, I first take the average of the "median growth rates of the median price per sqft" across March-August 2020 for each zip code, and then do nonparametric estimation.

Fact #7: The increase in the hotness of housing demand is particularly strong at the two ends of the zip code-level income distribution, displaying a U-shaped relationship. This pattern can be seen in Figure 8, which plots the nonparametric estimates of the median growth rate (year-on-year) of the median property views (a measure of housing demand) as a function of the median family income, during March-August 2020.[17] If we again disregard the segment for the extremely low income group, the year-on-year growth rate of housing demand decreases as we move up along the income distribution, from around 58 percent in zip codes with a median family income of $45,000 to about 37 percent in zip codes with $200,000. It then quickly rises again to about 50 percent (disregarding the far-right segment).

One possible explanation for this pattern is that it may reflect the liquidity constraints faced by low-income households, who were borrowing up to the debt-service limits before and are taking advantage of the ultra-easy monetary conditions to leverage up further. If that is indeed the case, then the financial stability concern would be stronger because the low-to-middle-income households are presumably less resilient to future shocks. Moreover, the high demand at the very high end of the income distribution could be explained by the particularly strong FOMO phenomenon, as these households have the financial means to afford the down payments for investment properties (as opposed to houses for residence purpose). Note that these two forces can reinforce each other: the higher housing prices caused by the speculative housing demand (from high-income households) push up the overall housing price index in the country, inducing low-income households to also expect higher future housing prices and thus rush to take mortgages and buy houses (in an attempt to avoid buying houses at higher prices in the future). Another possible explanation is analyzed below in the discussion of Fact #8.

C. Accounting for Urban Status

Several news articles have reported that urban residents in some areas are fleeing to the suburbs to seek more space and avoid the higher health risks in crowded urban neighborhoods.[18] If that is the case nationwide, then the above Fact #7 could also be explained by rich households buying second or larger homes in lower-income zip codes, which would have different economic and policy implications from those stated in the discussion of Fact #7.

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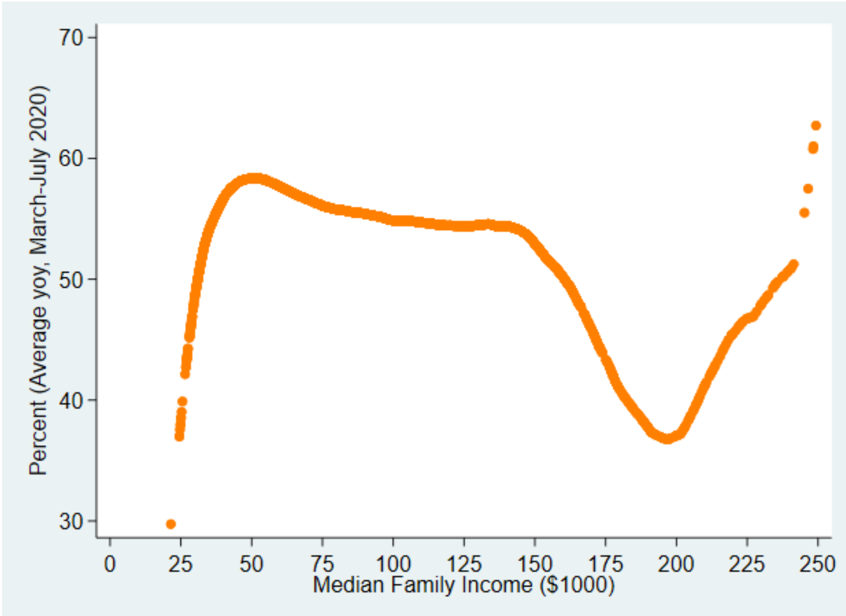
[17] A similar figure for the housing supply is not very informative due to the large amount of missing values for the supply indicator (and if we plot the supply for the non-missing observations, the results would not be comparable to those for the demand and price because of the different sample coverages). However, with the figures for price and demand, we can infer the dynamics for supply.

[18] One example is this article: "New Yorkers Are Fleeing to the Suburbs," *New York Times*, August 30, 2020.

Figure 8. Views per Property vs Median Family Income: Nonparametric Estimation



Source: realtor.com; American Community Survey; Author's calculations.

To test this, I merge the zip code-level realtor.com housing data with the urban status classification data provided by the US Department of Agriculture. Such data classifies all zip codes into metropolitan (of 50,000 or more people), micropolitan (of 10,000-49,999 people), small-town (of 2,500-9,999 people), and rural commuting areas based on the size and direction of the primary (largest) commuting/traffic flows.[19] The *suburb* areas mentioned in the news articles broadly correspond to micropolitan areas and small towns. The results are summarized in the following stylized fact.

Fact #8: The changes in housing price, demand, and supply since April 2020 are broad-based, with *similar* magnitudes of changes across metropolitan, micropolitan, small-town, and rural areas.

In terms of the housing price (Figure 9), all four geographic categories have experienced rapid accelerations, although *less* so in *small towns*. In metropolitan and micropolitan areas, the median housing price growth rates (y-o-y) accelerated from 4-4.5 percent in April 2020 to about 7 percent in August 2020 (i.e., an acceleration of 3-3.5 percentage points). In small towns, they

[19] There are actually ten more granular geographic categories, but for the purpose of this paper and to mitigate small-sample bias, I consider the four higher-level categories (metropolitan, micropolitan, small town, and rural areas). More details can be found at https://www.ers.usda.gov/data-products/rural-urban-commuting-area-codes.aspx.

accelerated from 3.5 percent in April to 5.3 percent in August (a 1.8 percentage point acceleration). And in rural areas, they accelerated from 3.5 percent to 6.0 percent (a 3.5 percentage point acceleration).

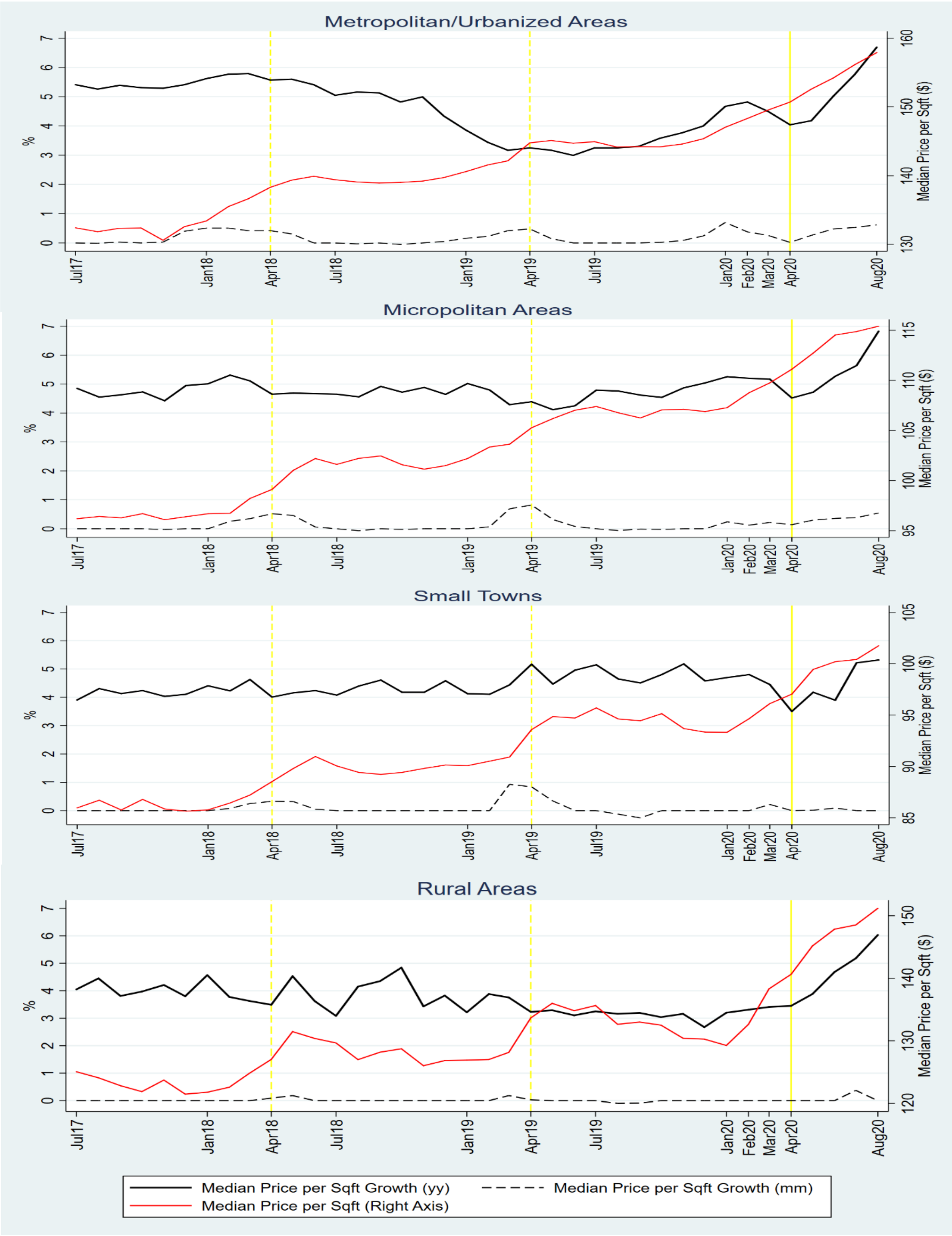
In terms of the housing demand (Figure 10), all four geographic categories have experienced rapid accelerations, although more so in rural areas. In metropolitan, micropolitan, and small towns, the median growth rates (y-o-y) of median property views accelerated from about 0 percent in April 2020 to about 125 percent or so in August 2020. And in rural areas, they accelerated to 178 percent in August.

In terms of the housing supply (Figure 11), the decreasing trends of the housing supply were amplified by COVID-19 in all four geographic categories, although less so in metropolitan and small-town areas. In metropolitan areas, the median growth rates (y-o-y) of median active listings went from -18 percent in April 2020 to -28 percent in August 2020 (by 10 percentage points). In micropolitan and rural areas, they went from about -10 percent in April to about -30 percent in August (by 20 percentage points). And in small towns, they went from -11 percent in April to -24 percent in August (by 13 percentage points).

In summary, the results suggest that the phenomenon of urban residents fleeing to the suburbs has not had a nationwide impact.[20] This suggests that the (nationwide) U-shaped housing demand across income distribution is unlikely to be driven by rich households buying houses in low-income zip codes; instead, it may indeed reflect the relaxed liquidity constraints for low-income households and the fear-of-missing-out for high-income households, both of which are associated with Fed's unprecedented easing.

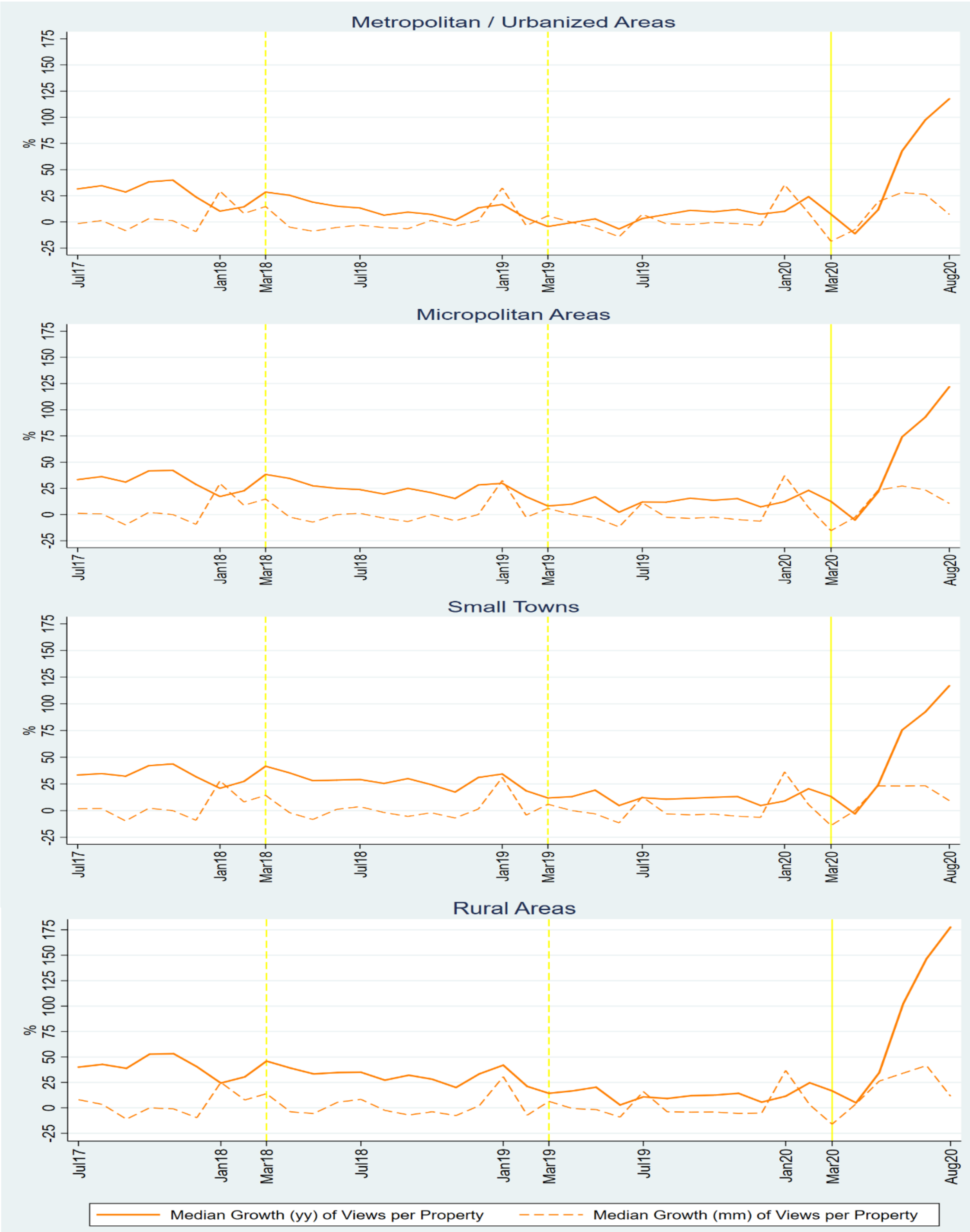
[20] Another possibility is that the increase in housing demand in urban areas (induced by, e.g., low mortgage rates and a preference shift from renting to owning houses) is so large that even after considering this fleeing effect, the urban housing demand and price have still increased substantially.

Figure 9. Median Housing Prices across Geographic Areas



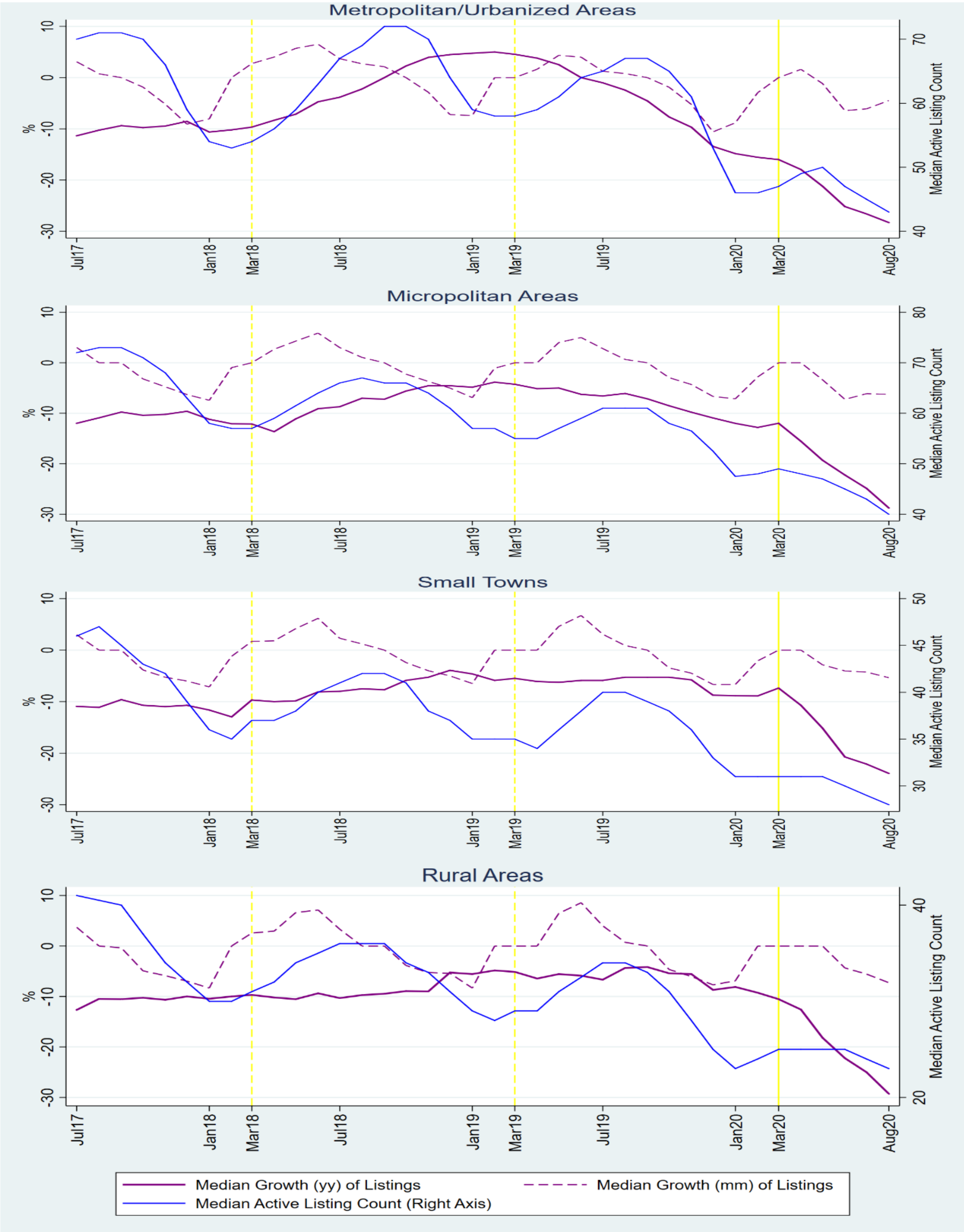
Source: realtor.com; US Department of Agriculture; Author's calculations.

Figure 10. Median Housing Demands across Geographic Areas



Source: realtor.com; US Department of Agriculture; Author's calculations.

Figure 11. Median Housing Supplies across Geographic Areas



Source: realtor.com; US Department of Agriculture; Author's calculations.

D. Accounting for Composition Effect

To mitigate the impact of the change in the housing supply composition, I restrict the sample to zip codes with little change in the median sqft of houses (no data on other property features are available to proxy for the quality of the house). In view of the small sample bias, I restrict to zip codes where the year-on-year median growth rates of the median sqft lie between -5 and 5 percent. Table 5 presents the summary statistics for the restricted sample, which are similar to those for the full sample.

Table 5. Summary Statistics after Cleaning for Zip Codes with Similar House Sizes

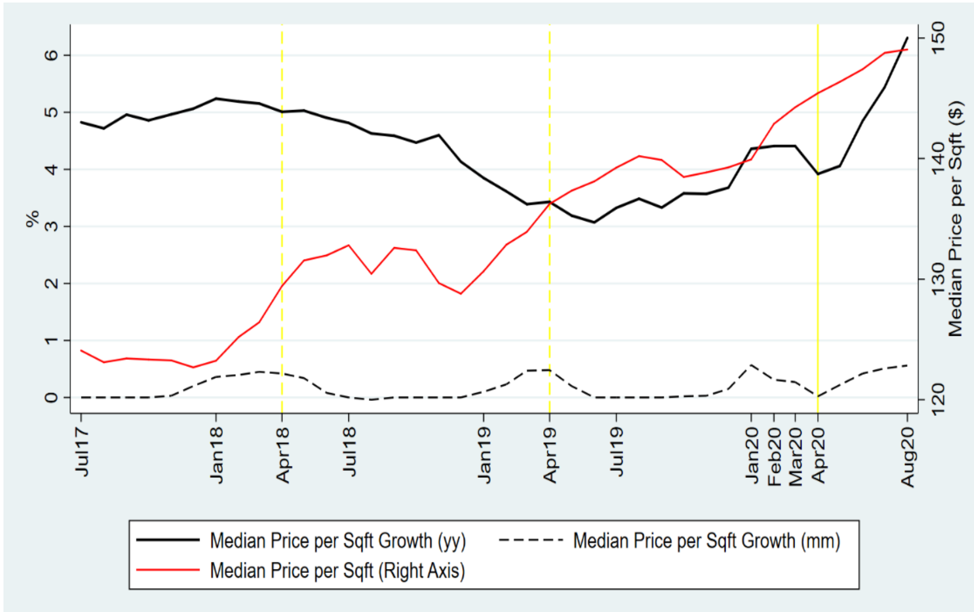
Variable	Unit	N	Mean	Min	Median	Max	SD
zip	NA	187,356	51,463	1,001	48,883	99,925	28,191
Month	NA	187,356	201,861	201,707	201,901	202,008	98
PropertyViews_yy	percent	187,356	26	-91	18	499	43
Listing_yy	percent	168,464	-4	-82	-8	470	27
MedianP_sqft_yy	percent	187,356	5	-96	4	199	11
MedianPrice_sqft	$	187,356	166	4	134	2,272	134
Median_sqft	NA	187,356	1,967	355	1,871	7,507	593
Median_sqft_yy	percent	187,356	0	-5	0	5	3
30Yr Fixed Mtg Rate	percent	187,356	4	3	4	5	1
MedianFamilyIncome	thousand $	186,671	78	10	71	249	30

Source: realtor.com; Freddie Mac; New York Fed; American Community Survey; Author’s calculations.

I find that the above eight stylized facts still hold after controlling for the composition/quality change of houses, five regarding aggregate evidence, two regarding distributional evidence, and one regarding the evidence across different geographic regions. Specifically:

Fact #1 with similar house sizes: After a temporary slow-down in March and April 2020, growth rates of the median housing price bounded back quickly and exceeded the growth rate before the COVID-19 crisis (Figure 12).

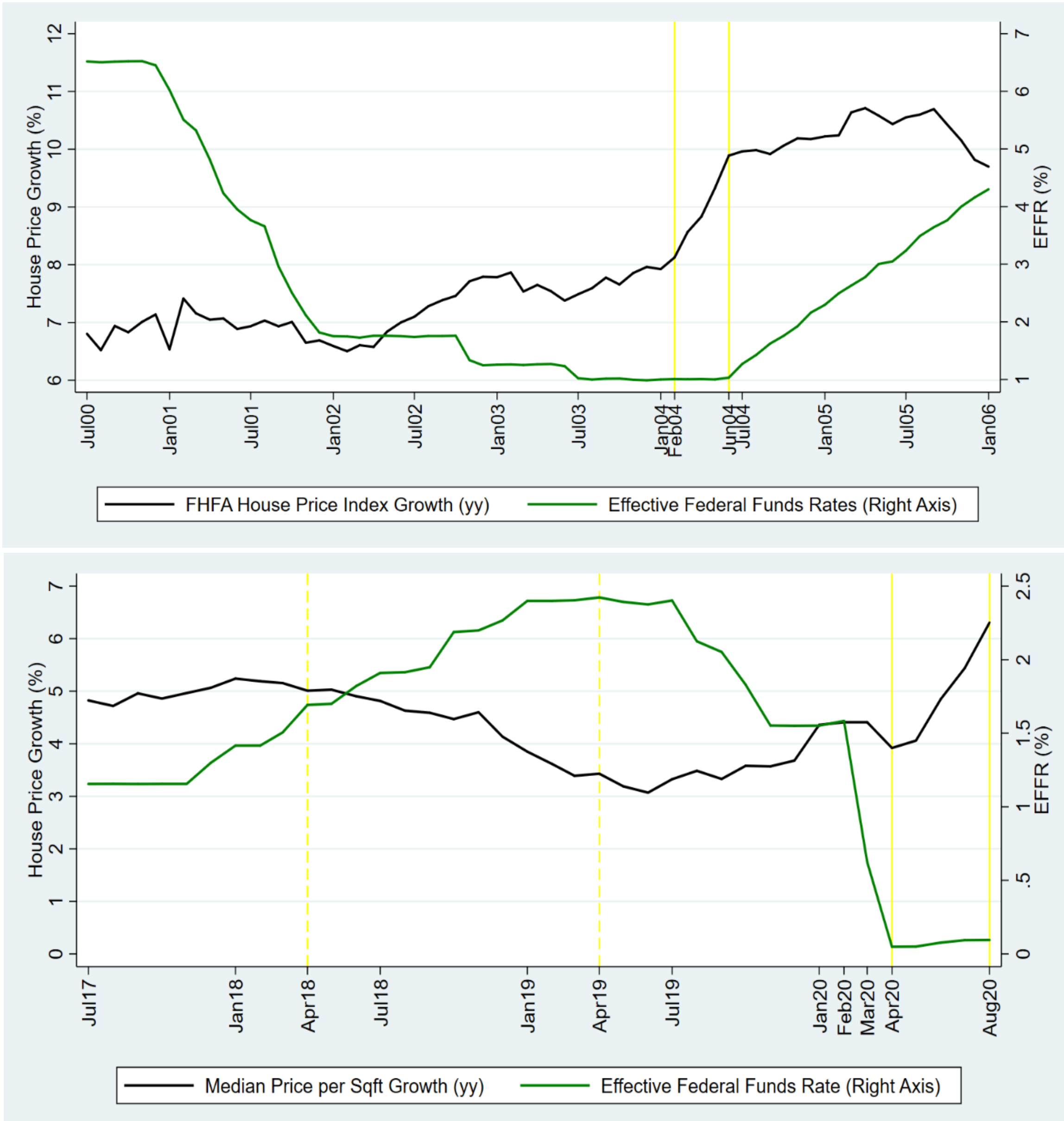
Figure 12. Median Housing Price: July 2017 – August 2020



Source: realtor.com; Author's calculations.

Fact #2 with similar house sizes: The year-on-year growth rates of the median price per sqft in the recent four months (April-August 2020) have accelerated *faster* than any four-month period in the lead-up to the 2007-09 GFC (Figure 13). During the four-month period after the Fed's ultra-easing, the year-on-year grow rates have accelerated by 2.4 percentage points (from 3.9 percent in April 2020 to 6.3 percent in August 2020), faster than the 1.8 percentage points observed from February 2004 to June 2004.

Figure 13. Housing Price Growth: Comparison between GFC and COVID



Source: FHFA; realtor.com; New York Fed; Author's calculations.

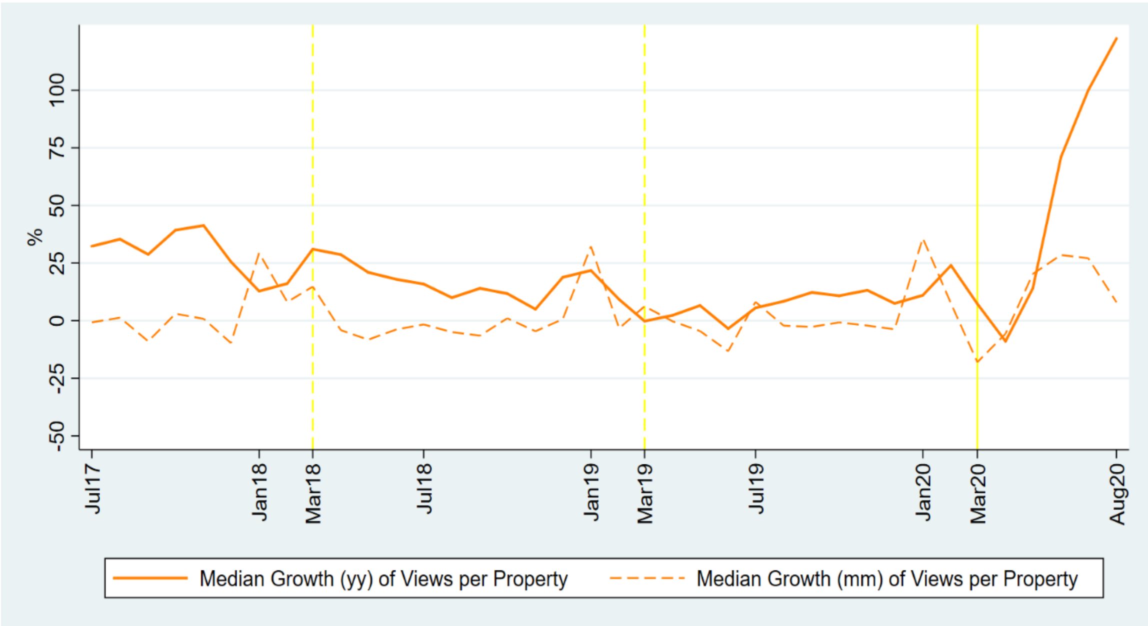
Fact #3 with similar house sizes: The decreasing trend of the housing supply since mid-2019 is amplified by COVID-19 (Figure 14).

Figure 14. Housing Supply/Listings: July 2017 – August 2020

Source: realtor.com; Author's calculations.

Fact #4 with similar house sizes: The hotness of housing demand, proxied by the online views per property, has been rising at an extraordinary rate since April 2020 (Figure 15).

Figure 15. Hotness of Housing Demand: July 2017 – August 2020



Source: realtor.com; Author's calculations.

Fact #5 with similar house sizes: The response of housing demand to mortgage rate displays a structural break, which is robust to falsification tests (Tables 6-7).

Table 6. Panel Regressions with Similar House Sizes

	(1) Views-YY FE All	(2) Views-YY FE Until Feb	(3) Views-YY FE Since March	(4) Views-YY Pool All	(5) Views-YY Pool Until Feb	(6) Views-YY Pool Since March
FRM_30Yr	-23.799**	-2.232	-268.867***	-22.271*	-1.292	-269.286***
	(0.042)	(0.561)	(0.004)	(0.058)	(0.754)	(0.004)
Constant	120.490**	29.481*	912.329***	114.395**	25.604	914.352***
	(0.016)	(0.084)	(0.003)	(0.023)	(0.161)	(0.002)
Observations	187,128	159,482	24,702	187,356	159,784	27,572
R-squared	0.264	0.297	0.773	0.067	0.000	0.408

Note: The dependent variable is the median year-on-year growth rates of hotness of housing demand; FRM_30Yr = 30-year fixed-rate mortgage; Standard errors are clustered at the month level, and *robust* p-values are in parentheses.
Source: Author's calculations.

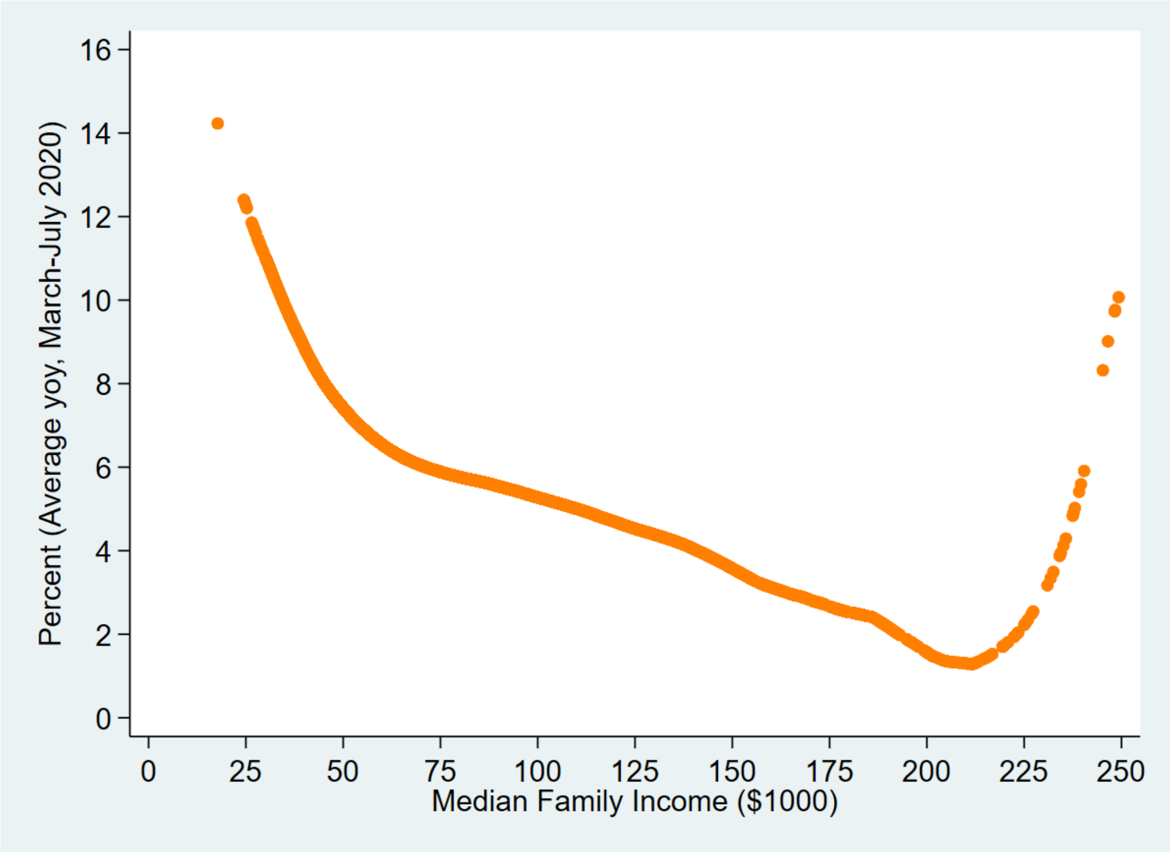
Table 7. Falsification Tests: Panel Regressions with Similar House Sizes

	(1) Views-YY FE Until August 2019	(2) Views-YY FE Until Feb 2019	(3) Views-YY FE March-August 2019	(4) Views-YY Pool Until August 2019	(5) Views-YY Pool Until Feb 2019	(6) Views-YY Pool March-August 2019
FRM_30Yr	-5.631	-22.222***	-8.197	-5.719	-23.272***	-5.836
	(0.380)	(0.000)	(0.291)	(0.420)	(0.000)	(0.377)
Constant	45.078	121.858***	38.697	45.454	126.418***	29.504
	(0.122)	(0.000)	(0.232)	(0.157)	(0.000)	(0.289)
Observations	129,250	99,077	27,439	129,699	99,743	29,956
R-squared	0.355	0.466	0.699	0.004	0.052	0.002

Note: The dependent variable is the median year-on-year growth rates of hotness of housing demand; FRM_30Yr = 30-year fixed-rate mortgage; *Robust* p-values are in parentheses.
Source: Author's calculations.

Fact #6 with similar house sizes: The increase in the housing price is particularly strong at the lower-to-middle end of the zip code-level income distribution (Figure 16).

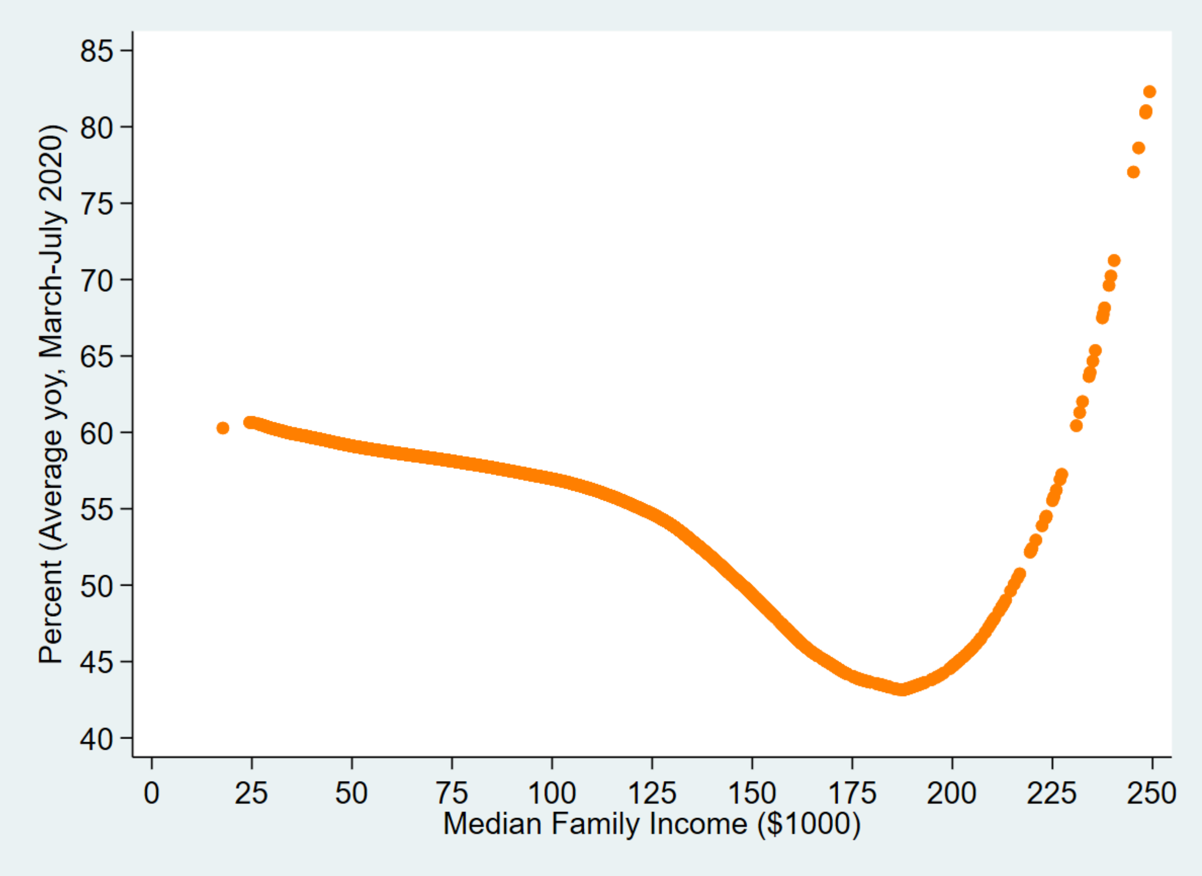
Figure 16. Price per Sqft Growth vs Median Family Income: Nonparametric Estimation



Source: realtor.com; American Community Survey; Author's calculations.

Fact #7 with similar house sizes: The increase in the hotness of housing demand is particularly strong at the two ends of the zip code-level income distribution, displaying a U-shaped relationship (Figure 17). With a narrower and potentially more comparable sample, the U-shaped relationship is actually more visible than the one with the full sample. The year-on-year growth rate of the housing demand measure decreases from around 60 percent in zip codes with a median family income of $25,000 to about 43 percent in zip codes with $190,000. It then quickly rises again to about 70 percent (disregarding the far-right segment).

Figure 17. Views per Property vs Median Family Income: Nonparametric Estimation



Source: realtor.com; American Community Survey; Author's calculations.

Fact #8 with similar house sizes: The changes in housing price, demand, and supply since April 2020 are broad-based, with *similar* magnitudes of changes across metropolitan, micropolitan, small-town, and rural areas. The figures are very similar to Figures 9-11, so they are omitted for brevity.[21]

E. Accounting for Mobility

Besides the aforementioned composition effect, another concern is: the observed extraordinarily high growth rates of housing demand in the COVID era may be simply caused by the much lower outdoor mobility (associated with the stay-at-home orders) and much more frequent

[21] They are available upon request. After restricting the sample to zip codes with similar house sizes, the only major difference is for the house price in rural areas, which show that the median house price growth rate (y-o-y) came back to 3 percent in August 2020. However, this is most likely due to the small-sample bias (with only 246 observations in August 2020), so the full-sample version of the result for rural area's house price growth may be more reliable.

internet viewing in general, rather than an indication of the higher "genuine" housing demand associated with the record-low interest rates.

However, there is a second force at play: the stay-at-home orders (and the worsening of the pandemic itself) also imply more disruptions to the housing search and bidding processes, which *decrease* households' incentives to spend time in viewing houses online right now when they believe it is unsafe to view the houses in person and proceed with the purchasing process. This is the force emphasized by D'Lima, Lopez, and Pradhan (2020), who argue that "shutdown orders affect the process of buyers and sellers matching up for prospecting properties and subsequently completing the sale. Such frictions can be characterized as causing a demand side shock wherein buyers are unable to conduct an optimal search and bidding process."

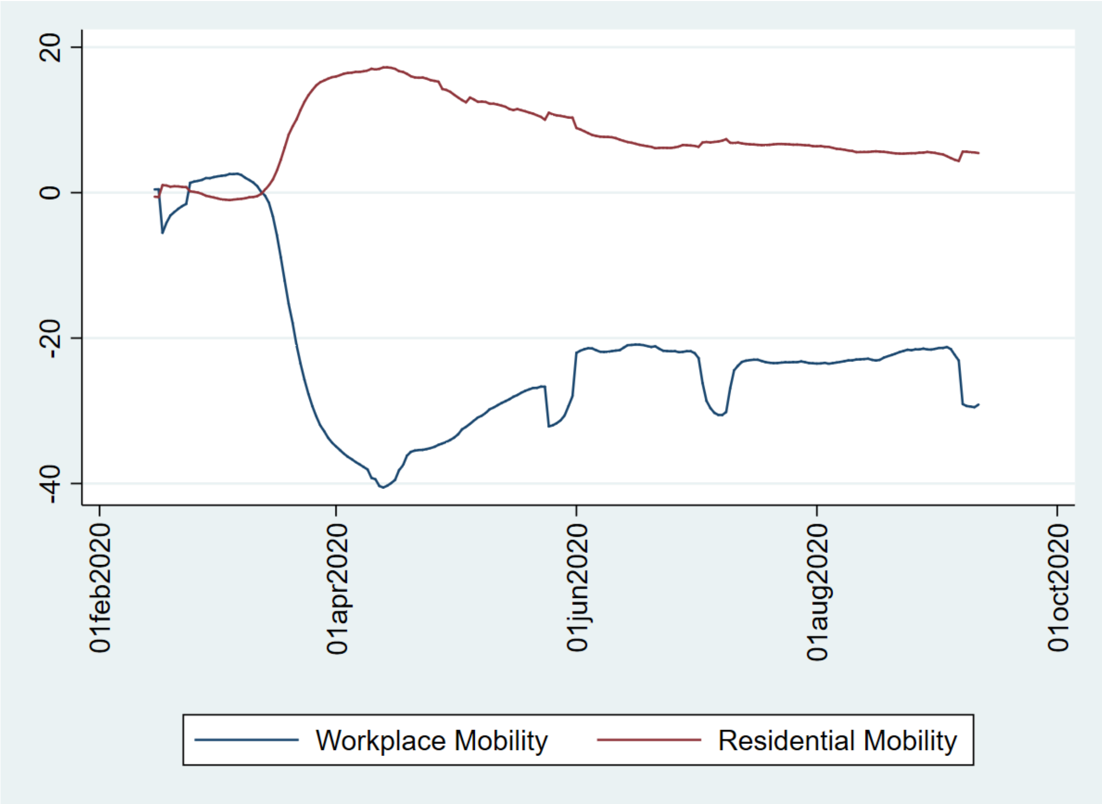
Therefore, it is unclear which of the two forces would dominate and whether the omission of the mobility variable would significantly lower the usefulness of the online views in proxying housing demand. To empirically address this, I merge the zip code-level monthly housing data with the county-level daily Google mobility data (averaged to monthly) and rerun the housing demand regressions. To ensure the robustness of the results, I use several mobility measures, including the workplace mobility, residential mobility, and overall mobility that also accounts for grocery, recreation activities, etc. These daily indicators measure how visits and length of stay at different places change compared to the baseline (which is the 5-week period during January 3–February 6, 2020).[22] To mitigate the impact of the composition change, I still restrict the sample to zip codes where the year-on-year median growth rates of the median sqft lie between -5 and 5 percent. The results for zip codes with -2 and 2 percent growth rates are very similar and are available upon request.

As shown in Table 8, across both specifications (fixed-effect and pooled regression models), workplace mobility is positively correlated with online views per property (so is overall mobility), and residential mobility is negatively correlated. Therefore, during the stay-at-home period when workplace mobility is lower and residential mobility is higher (as indicated in the daily time series in Figure 18), the online views per property tend to be *lower*, all else being equal. These results provide suggestive evidence that the aforementioned second force dominates the first one, and that the observed unusually high growth in online views per property since March 2020 may indeed be driven by the historically low interest rates.

[22] For the data and detailed documentation, see https://www.google.com/covid19/mobility/.

Figure 18. Google Mobility in the US: February 15 – September 11, 2020

(7-day moving average)



Source: Google; Author's calculations.

To address a related concern that the signs of these mobility indicators may just reflect the impacts of the outbreak dynamics or the negative shocks on the macroeconomy, I further control for the (composite) Purchasing Managers' Index (PMI), which is available at monthly frequency until August 2020. Since the original PMI data are reported relative to the previous month, with above 50 being expansion and below 50 being contraction, I normalize them to absolute levels (with the PMI in July 2016 equal to 100) and then calculate the year-on-year growth for each month during July 2017-August 2020. The results are reported in Table 9: For four out of the six columns (4-6), both the mobility indicator and the PMI are significant; Moreover, workplace mobility is still positively correlated with the housing demand measure, and residential mobility is still negatively correlated, even after controlling for PMI, a measure of the overall macroeconomy. As a side note, consistent with previous discussions on omitted variable bias, the impact of the mortgage rate on housing demand becomes much stronger after controlling for the macroeconomic performance (262-341 in Table 9, as opposed to 202-265 in Table 8).

Note that because the Google mobility data starts from February 2020, it is *not* possible to analyze the existence of a structural break (in March 2020) in the housing demand response to lower interest rates. However, the estimated mortgage rate elasticities (in Table 9) after controlling for the mobility indicators are comparable with, and in some cases larger than, those without these controls (the "Since March" columns in Table 6).

Table 8. Panel Regressions with Similar House Sizes and Mobility Indicators

(February 2020 – August 2020)

	(1) Workplace FE	(2) Residential FE	(3) Overall FE	(4) Workplace Pool	(5) Residential Pool	(6) Overall Pool
FRM_30Yr	-264.645***	-223.346***	-201.779***	-251.646***	-221.336***	-204.501***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Workplace	2.531***			1.851***		
	(0.000)			(0.000)		
Residential		-5.236***			-3.808***	
		(0.000)			(0.000)	
Overall			1.990***			1.013***
			(0.000)			(0.008)
Constant	981.441***	825.775***	714.664***	919.132***	804.548***	716.835***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	20,327	19,090	16,072	22,044	20,664	17,380
R-squared	0.806	0.810	0.789	0.439	0.442	0.411

Note: The dependent variable is the median year-on-year growth rates of hotness of housing demand; FRM_30Yr = 30-year fixed-rate mortgage; Workplace, Residential, Overall are workplace mobility, residential mobility, and overall mobility from Google; *Robust* p-values are in parentheses.
Source: Author's calculations.

Table 9. Panel Regressions with Similar House Sizes, Mobility Indicators, and PMI
(February 2020 – August 2020)

	(1) Workplace FE	(2) Residential FE	(3) Overall FE	(4) Workplace Pool	(5) Residential Pool	(6) Overall Pool
FRM_30Yr	-313.395***	-261.913***	-312.828***	-334.613***	-311.265***	-340.559***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
PMI_yy	0.315	0.208	0.554**	0.500*	0.482*	0.693***
	(0.227)	(0.439)	(0.024)	(0.056)	(0.074)	(0.009)
Workplace	1.900***			1.175***		
	(0.008)			(0.005)		
Residential		-4.313***			-2.314***	
		(0.006)			(0.008)	
Overall			1.252***			0.608***
			(0.006)			(0.002)
Constant	1,129.149***	946.864***	1,084.556***	1,181.306***	1,093.530***	1,173.619***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	20,327	19,090	16,072	22,044	20,664	17,380
R-squared	0.811	0.811	0.811	0.459	0.458	0.464

Note: The dependent variable is the median year-on-year growth rates of hotness of housing demand; PMI_yy is the year-on-year growth of the normalized PMI index; FRM_30Yr = 30-year fixed-rate mortgage; Workplace, Residential, Overall are workplace mobility, residential mobility, and overall mobility from Google; *Robust* p-values are in parentheses.
Source: Author’s calculations.

V. Conclusion and Policy Implications

Motivated by the unprecedented monetary easing, the plunging mortgage rates, and anecdotal evidence about the rapidly-rising residential housing prices, I document eight stylized facts on the COVID-era US housing market based on results from structural break models and nonparametric estimation, including both aggregate and distributional facts. One surprising result on the *aggregate* front is that the growth rate of the median housing price during the four months (April-August 2020) since Fed’s unprecedented monetary easing has accelerated faster than the fastest four-month acceleration in the lead-up to the GFC. On the *distributional* front, I find that both the year-on-year growth rate of housing price and that of housing demand are higher at the lower-income zip codes, possibly reflecting relaxed liquidity constraints for low-income households (who were borrowing up to the debt-service limits before the monetary easing). In particular, I find that this (nationwide) result is unlikely driven by urban residents fleeing to the suburbs, as the changes in housing price, demand, and supply since April 2020 have similar magnitudes across metropolitan, micropolitan, small-town, and rural areas. These results are robust after accounting for the composition change in housing supply and the mobility change of households during the COVID era.

Most of the results are stylized facts that do not rely on stringent modeling assumptions, although they can be interpreted in various ways. For example, in terms of the aggregate results, as discussed in Section IV(A), they are consistent with both Scenario (a) *(fear of missing out scenario)*, where potential homebuyers may be rushing to the housing market to take advantage of the historically low mortgage rate, and Scenario (b) *(COVID-induced behavioral change scenario)*, where households now value homeownership higher and are also more able to afford the down payments due to higher forced savings.

Hence, further studies are needed to more closely examine these areas. For example, given that the aforementioned two scenarios involve different nature of behavior (Scenario (a) involves more speculative, unsustainable housing demand, and Scenario (b) involves more fundamental housing demand), it is important to empirically tease out which scenario plays a more dominant role in the current conjuncture, and to theoretically simulate their implications on household leverage, financial stability, resource allocation across sectors, and the medium-to-long-run economic growth. Controlling for the omitted variables discussed in Section IV(A) may be one step forward towards this goal. And to shed more light on the distributional effect, one possible approach is to merge with data on homebuyers' incomes (at least at the zip code level) to quantitatively assess the drivers for the high growth in housing demand in low-income areas.

Despite the need for further work, hereby I still lay out some preliminary policy implications to stimulate more discussions. In view of the *aggregate* evidence, the results highlight the importance of complementing monetary easing (needed for combating the COVID crisis) by implementing carefully-designed *macroprudential* policies, such as enforcing loan documentation requirements and stringent limits on loan-to-value ratio, debt-to-income ratio, and debt-service-to-income ratio. Of course, as noted earlier, there are many complex forces driving the US housing market, and the rapid acceleration of housing price growth may slow down, e.g., after the housing supply returns to normal. Besides, the US financial system appears to be more resilient now than the pre-GFC period, as evidenced by the strong stress test results released on

June 25, 2020.[23] Moreover, the role of the Fed's low-interest-rate policy in driving the GFC appears to be debatable, as discussed in the literature review section.

However, the consensus among the vast majority of literature seems to be thatthe loosening in mortgage lending standards, the implicit government guarantee in the housing finance system, as well as the feedback loop between rapid credit provision and rising housing prices had played a major role in fueling the housing boom in the lead-up to the GFC. And all these forces coexisted with an extended period of low federal funds rates back then. Therefore, in the current environment where the rates are even lower, the implicit government mortgage guarantee is still present, and the housing price growth so far has accelerated at a faster pace than the pre-GFC era, macroprudential regulations and close scrutiny of bank/nonbank mortgage lending would be crucial to prevent the GFC history from repeating itself.

In view of the *distributional* evidence, the optimal policy design faces a difficult trade-off. On the one hand, from the perspective of lowering systemic risks, it is advisable not to relax the underwriting standards for new homebuyers, particularly when households with low or volatile incomes appear to be more actively seeking home purchase and mortgage borrowing during the monetary easing. On the other hand, from the perspective of reducing inequality, it is also essential to ensure that those who have experienced COVID-related employment disruptions are able to benefit from the historically low rates. On balance, the *"streamlined" refinance programs* proposed by Gerardi and others (2020), which allow existing homeowners to refinance and cut monthly payment without the need to document employment/income, seem to be an appealing option. Assuming that the existing low-income homeowners are less risky than the low-income renters, such programs could help a subgroup of low-income households (i.e., low-income homeowners) benefit from the low rates and contribute to reducing the *between-group* inequality.

Moreover, given my finding that the low-income zip codes are experiencing higher growth in housing price and if future studies confirm that this is mainly driven by local homeowners (rather than by well-off households buying houses in low-income areas), then it means low-income homeowners may be benefiting from the easy financing conditions more than

[23] Vice Chair Randal Quarles concluded that "The banking system has been a source of strength during this crisis." See Federal Reserve Board (2020) and the summary here: https://www.federalreserve.gov/newsevents/pressreleases/bcreg20200625c.htm.

low-income renters. In that case, *targeted* financial assistance to renters could be helpful for reducing the *within-group* inequality between these two low-income subgroups. One example of such assistance is the renter direct payment program as discussed in Goodman and Magder (2020), where payments are made in a voucher form or directly to property owners (to ensure the rent payments are used as intended).

APPENDIX

Appendix Table 1. Number of Observations across All Months (after Cleaning)

Month	Frequency	Percent	Cumulative
201707	12,927	2.6	2.6
201708	12,961	2.6	5.2
201709	12,979	2.6	7.9
201710	12,988	2.6	10.5
201711	12,483	2.5	13.0
201712	12,655	2.6	15.6
201801	12,479	2.5	18.1
201802	12,533	2.5	20.7
201803	12,664	2.6	23.2
201804	12,755	2.6	25.8
201805	12,886	2.6	28.4
201806	13,105	2.7	31.1
201807	13,175	2.7	33.7
201808	13,205	2.7	36.4
201809	13,265	2.7	39.1
201810	13,233	2.7	41.8
201811	13,183	2.7	44.4
201812	13,113	2.7	47.1
201901	12,954	2.6	49.7
201902	12,890	2.6	52.3
201903	13,089	2.7	55.0
201904	12,959	2.6	57.6
201905	13,063	2.6	60.2
201906	13,219	2.7	62.9
201907	13,265	2.7	65.6
201908	13,374	2.7	68.3
201909	13,418	2.7	71.0
201910	13,565	2.8	73.8
201911	13,610	2.8	76.5
201912	13,623	2.8	79.3
202001	13,738	2.8	82.1
202002	13,262	2.7	84.8
202003	13,022	2.6	87.4
202004	12,918	2.6	90.0
202005	12,790	2.6	92.6
202006	12,477	2.5	95.1
202007	12,195	2.5	97.6
202008	11,936	2.4	100.0
Total	493,956	100.0	

Source: Author's calculations.

REFERENCE

Acharya, Viral V. and Sascha Steffen. 2020. "The Risk of Being A Fallen Angel and the Corporate Dash for Cash in the Midst of COVID." *COVID Economics*, 10: 44–61.

Acharya, Viral V., Matthew Richardson, Stijn Van Nieuwerburgh, and Lawrence J. White. 2011. "*Guaranteed To Fail: Freddie, Fannie, and the Debacle of U.S. Mortgage Finance*," Princeton University Press.

Ambrus, Attila, Erica Field, and Robert Gonzalez. 2020. "Loss in the Time of Cholera: Long-run Impact of A Disease Epidemic on the Urban Landscape," *American Economic Review*, 110, 475–525.

Bayoumi, Tamim, and Yunhui Zhao. 2020. "Incomplete Financial Markets and the Over-Development of the Chinese Housing Sector," IMF Working Paper.

Barro, Robert J., José F. Ursúa, Joanna Weng. 2020. "The Coronavirus and the Great Influenza Pandemic: Lessons from the 'Spanish Flu' for the Coronavirus's Potential Effects on Mortality and Economic Activity," *NBER Working Paper No. 26866.*

Bolhuis, Marijn, and Judd N. L. Cramer. 2020. "Baby Boomers and the Housing Market on the Cusp of COVID-19," arXiv preprint arXiv: 3102262.

Bronka, Patryk, Diego Collado, and Matteo Richiardi. 2020. "The Covid-19 Crisis Response Helps the Poor: The Distributional and Budgetary Consequences of the UK Lockdown," *COVID Economics*, 26: 79–106.

Chen, Sophia, Deniz Igan, Nicola Pierri, and Andrea F. Presbitero. 2020. "Tracking the Economic Impact of COVID-19 and Mitigation Policies in Europe and the United States," *COVID Economics*, 36: 1–24.

Chetty, Raj, John N. Friedman, Nathaniel Hendren, Michael Stepner, and the Opportunity Insights Team. 2020. "How Did COVID-19 and Stabilization Policies Affect Spending and Employment? A New Real-Time Economic Tracker Based on Private Sector Data," Working Paper.

Correia, Sergio. 2016. "A Feasible Estimator for Linear Models with Multi-Way Fixed Effects," Duke University Working Paper.

Correia, Sergio, Stephan Luck, and Emil Verner. 2020. "Pandemics Depress the Economy, Public Health Interventions Do Not: Evidence from the 1918 Flu," Working Paper.

Deb, Pragyan, Davide Furceri, Jonathan D. Ostry, and Nour Tawk. 2020. "The Economic Effects of Covid-19 Containment Measures," *Covid Economics*, 24: 32–75.

D'Lima, Walter, Luis A. Lopez, and Archana Pradhan. 2020. "COVID-19 and Housing Market Effects: Evidence from U.S. Shutdown Orders," *SSRN Working Paper No. 3647252.*

Dokko, Jane, Brian M. Doyle, Michael T. Kiley, Jinill Kim, Shane Sherlund, Jae Sim, Skander Van Den Heuvel. 2011. "Monetary policy and the global housing bubble," *Economic Policy*, Volume 26, Issue 66(1): 237–287.

Domanski, Dietrich, Scatigna, Michela, and Anna Zabai. 2016. "Wealth Inequality and Monetary Policy," *BIS Quarterly Review*.Elenev, Vadim, Tim Landvoigt, and Stijn Van Nieuwerburgh, 2020, "Can The Covid Bailouts Save The Economy?" *NBER Working Paper No. 27207.*

Francke, Marc, and Matthijs Korevaar. 2020. "Housing Markets in a Pandemic: Evidence from Historical Outbreaks," Working Paper.

Davide Furceri, Prakash Loungani, Jonathan D. Ostry and Pietro Pizzuto. 2020. "Will Covid-19 Affect Inequality? Evidence from Past Pandemics," *COVID Economics*, 12: 138–157.

Furceri, Davide, Prakash Loungani, and Aleksandra Zdzienicka. 2018. "The Effects of Monetary Policy Shocks on Inequality," *Journal of International Money and Finance,* 85: 168–186.

Galletta, Sergio, and Tommaso Giommoni. 2020. "The Effect of the 1918 Influenza Pandemic on Income Inequality: Evidence from Italy," *COVID Economics*, 33: 73–109.

Gerardi, Kristopher, Lara Loewenstein, and Paul Willen. 2020. "Evaluating the Benefits of a Streamlined Refinance Program," *Federal Reserve Bank of Atlanta Policy Hub, No. 08-2020.*

Glover, Andrew, Jonathan Heathcote, Dirk Krueger, and José-Víctor Ríos-Rull. 2020. "Health versus Wealth: On the Distributional Effects of Controlling A Pandemic," *COVID Economics,* 6: 22–64.

Goodman, Laurie, and Dan Magder. 2020. "Avoiding a COVID-19 Disaster for Renters and the Housing Market," Washington, DC: Urban Institute.

Greenwald, Daniel L., John Krainer, and Pascal Paul. 2020. "The Credit Line Channel," *Federal Reserve Bank of San Francisco Working Paper Series.*

Guimarães, Paulo, and Pedro Portugal. 2010. "A Simple Feasible Procedure to Fit Models with High-Dimensional Fixed Effects," *Stata Journal* 10 (4). College Station, TX: Stata Press:628–64922.

Hohberger, Stefan, Romanos Priftis, and Lukas Vogel. 2020. "The Distributional Effects of Conventional Monetary Policy and Quantitative Easing: Evidence from An Estimated DSGE Model," *Journal of Banking and Finance*, 113, 105483.

Keys, Benjamin J., Tanmoy Mukherjee, Amit Seru, and Vikrant Vig. 2010. "Did Securitization Lead to Lax Screening? Evidence from Subprime Loans." *Quarterly Journal of Economics*, 125 (1): 307-362.

Keys, Benjamin J., Amit Seru, and Vikrant Vig. 2012. "Lender Screening and the Role of Securitization: Evidence from Prime and Subprime Mortgage Markets." *Review of Financial Studies*, 25 (7): 2071-2108.

Ling, David C., Chongyu Wang and Tingyu Zhou. 2020. "A First Look at the Impact of COVID-19 on Commercial Real Estate Prices: Asset-Level Evidence," *COVID Economics*, 22: 205-260.

McDonald, John F., and Houston H. Stokes. 2013. "Monetary Policy and the Housing Bubble," *Journal of Real Estate Finanance and Economics*, 46: 437–451.

Merrouche, Ouarda, and Erlend W. Nier. 2010. "What Caused the Global Financial Crisis - Evidence on the Drivers of Financial Imbalances 1999-2007," *IMF Working Paper No. 10/265*.

Palomino, Juan C., Juan G. Rodríguez, and Raquel Sebastian. 2020. "Wage Inequality and Poverty Effects of Lockdown and Social Distancing in Europe," *COVID Economics*, 25: 186–229.

Romem, Issi. 2019. "The Silver Tsunami: Which Areas will be Flooded with Homes once Boomers Start Leaving Them?" *Zillow Research*.

Schmitt-Grohé, Stephanie, Ken Teoh, and Martín Uribe. 2020. "Covid-19: Testing Inequality in New York City," *COVID Economics*, 8: 27–43.

Wong, Grace. 2008. "Has SARS Infected the Property Market? Evidence from Hong Kong," *Journal of Urban Economics*, 63, 74–95.

Zhao, Yunhui. 2019. "Evidence of Government Subsidy on Mortgage Rate and Default: Revisited," *Journal of Housing Research*, 28(1): 23–49.

Zhao, Yunhui. 2020. "Got Hurt for What You Paid? Revisiting Government Subsidy in the U.S. Mortgage Market," *SSRN Working Paper No. 2895822.*