Distribution Agreement

Understanding Housing Market Boom During COVID-19:
Distributional Effect on Housing Demand Among Income Groups

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An abstract of
a thesis submitted to the Faculty of Emory College of Arts and Sciences
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Abstract

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Exploiting ZIP-by-month variation, this paper examines the distributional effect of the COVID-19 pandemic on housing demand across income groups. First, we document heterogeneous demand responses to pandemic shocks. We show a large increase in demand growth rate from high-income ZIP-codes during the first six months of the pandemic. The result holds true after controlling for the housing supply effect, the state-level effect, and the county-level effect. Second, we develop within-group models testing the effects of two speculation channels. We find little evidence that the strong demand response in high-income ZIP-codes is driven by fast-growing housing prices; instead, we estimate that the ultra-low mortgage rates play an important role. With prolonged pre-pandemic and post-pandemic coverage, this paper sheds light on the implications for the evolution of wealth inequality in the United States.

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" All things are possible to him that believeth. " (Mark 9:23)

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Contents

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1 Introduction

The COVID-19 pandemic is unprecedented in its global reach and impact, involving simultaneous disruptions to both supply and demand in an interconnected world economy. In the United States, the contraction and uncertainty posed formidable challenges to policymakers, when the Federal Reserve stepped in with a broad array of actions[1].

Against the backdrop of a significantly altered economic landscape, the US residential housing market is experiencing a boom [2]. On the price side, housing prices are rising quickly

[1] Fed's actions include consecutive federal funds rate cuts, massive purchase of MBS, etc.

[2] The home equity experienced a large increase. According to CoreLogic (NYSE: CLGX), homeowners gained over $1.5 Trillion in Equity in 2020. The average annual equity gain of Q4 2020 was highest since Q4 2013. More details see https://www.corelogic.com/press-releases/home-equity-continues-to-soar-homeowners-gained-over-1-5-trillion-in-equity-in-2020-corelogic-reports/

across the country (Figure 8 upper-left panel). After a temporary slow-down in the beginning of the pandemic, both the monthly price growth rate (Figure 8 upper-right panel) and the yearly price growth rate (Figure 8 lower-left panel) regained the momentum and exceeded the pre-pandemic levels. On the supply side, the downward trend in housing supply is in conjunction with the upward trend of housing prices. The pandemic further amplified the decreasing trend of housing supply yearly growth rate (Figure 9 lower-left panel).

The rising prices and the decreasing supply characterize the residential housing market during the pandemic, where there is a small emergent literature.

On the general housing market, Balemi et al (2021) provide an overview of the pandemic effects and each real sector's performance in the US. B. Wang (2021) conducts a cross-city analysis to study the effect of pandemic on housing prices. Gamber et al (2021) examines the housing demand and explores the drivers of housing price. For markets outside of the US, Cheung et al (2021), Qian et al (2021), and Bayoumi and Zhao (2020) focus on the Chinese market, whereas De Toro et al (2021) and Del Giudice et al (2020) conduct studies on the Italian market.

In sub-markets, there are papers covering the *commercial real estate* (CRE) markets and *mortgage* markets. On the CRE side, Ling et al (2020) study the effect of pandemic on real estate prices; Wang and Zhou (2021) study the relationship between tenants' resiliency and firms' performance. On the mortgage market side, Agarwal et al (2020) study the relationship between income and savings from mortgage refinancing, while An et al (2021) focus on mortgage delinquency and forbearance. Cherry et al (2021) also studies debt forbearance during the COVID-19 pandemic.

Narrowing down to the US *residential* real estate market, D'Lima et al (2020) focus on the government's shutdown policies with a difference-in-difference model. They propose that there are moderate *aggregate* pricing effects but a significant decrease in sales during the shutdown and re-opening periods. Zhao (2020) studies the residential housing markets *before August 2020* and provides eight stylized results both on the aggregate side and the distributional side. The distributional results come from *non-parametric estimation*, pointing out potential unintended consequences of pandemic-fighting policies.

Complementing the existing literature, this paper focuses on the distributional effect of housing demand in the US residential housing market for a prolonged time from January 2019 to January 2022.

Specifically, with the pattern of housing demand among income groups shown in Figure 1, this paper works on two main questions. First, what would be the impacts of COVID-19 on housing demand among different income groups? Second, what would be the main driving forces of the housing demand pattern among different income groups?

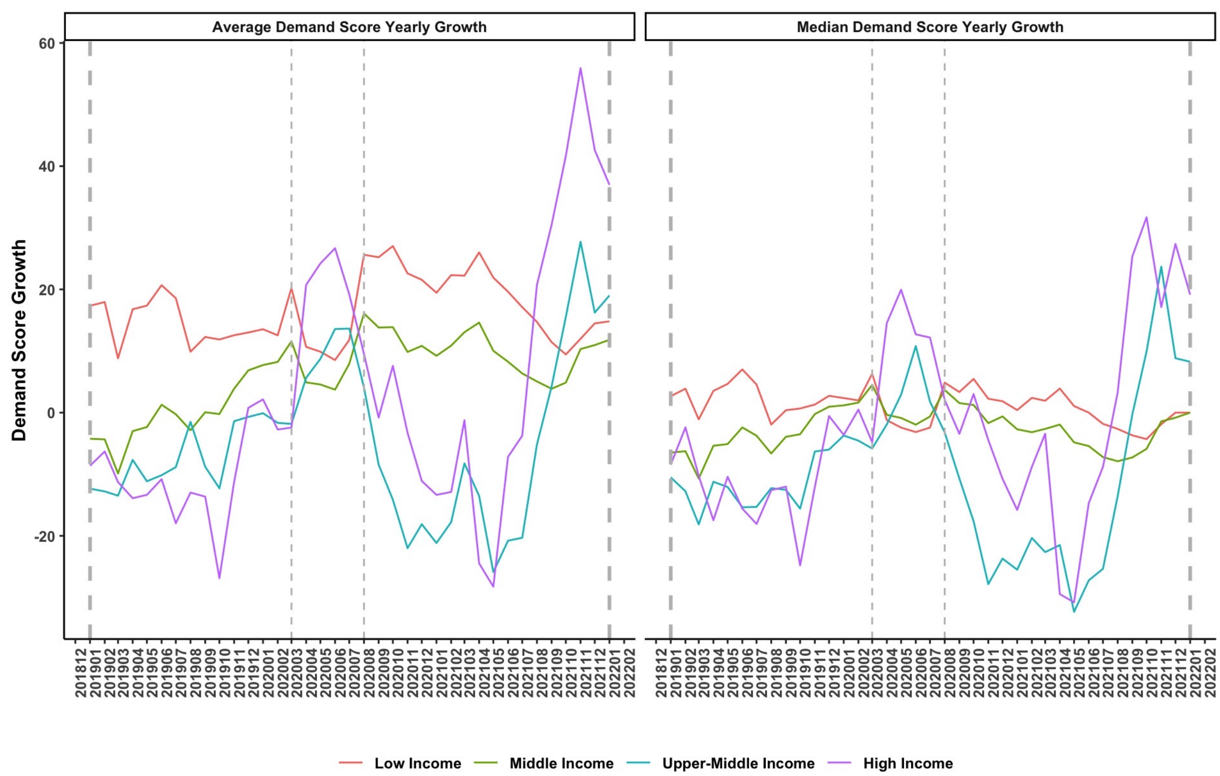

Figure 1: Housing Demand Growth from January 2019 to January 2022

To empirically address the questions, we construct a ZIP-by-month panel data by aggregating a mixture of proprietary and public use data sources. Our strategy exploits cross-sectional variation across ZIP-codes in ex-ante pandemic median household income to isolate the effect of the COVID-19 pandemic from aggregate macroeconomic shocks. First, we follow the housing demand yearly growth through time to determine how the pandemic affected the distributional pattern of housing demand across income groups. Second, based on the pattern observed, we further assess the effect of two market drivers on the altered housing demand pattern during the pandemic.

A total of twelve models are used to perform our empirical strategy. With Model 1 to Model 4 (sample-level regressions), we derive that the increase in housing demand is particularly strong in the upper-middle-income ZIPs and high-income ZIPs during the first six months of pandemic. The results remain robust after controlling for the housing supply composition effect, the state-level effect, and the county-level effect. With Model 5 to Model 12 (income group-level regressions), we provide suggestive evidence that the surged housing demand yearly increase in upper-middle-income ZIPs and high-income ZIPs is driven by ultra-low interest rates.

Structure of the Paper The rest of the paper is organized as follows. In section 2, we explain our data and methodology. In Section 3, we report our results on the distributional pattern of housing demand. In Section 4, we present results from models testing the effects of two speculation channels on the distributional pattern. Section 5 concludes. The Appendix contains some further results and robustness exercises.

2 Data, Summary Statistics, and Methodologies

This section provides an overview of the main data sources for our analysis, discusses construction of key variables, and presents summary statistics.

2.1 Data Sources

We construct a ZIP-by-month panel by aggregating a mixture of proprietary and public use data sources. The housing data are merged with the ex-ante pandemic median household income, the monthly mortgage rates data, and the daily national effective federal funds rate data. In addition, three data sources are used to crosswalk ZCTA codes, ZIP codes, counties, and states.

Housing Data The housing data are from anonymized zip-code level monthly panel databases released in the realotor.com library [3], covering most zip codes in the US from July 2017 to January 2022. Two sub-databases are used to shed light on the residential housing market from both the supply side and the demand side. The two sub-databases at focus are realtor.com residential listings database for market levels and realtor.com market hotness index database for housing demand. The residential listings database is also available at a weekly frequency on the national and metro levels, while the hotness index data are solely available at a monthly frequency. To ensure the coherency of data on the supply and the demand sides, this study uses monthly data for both databases.

Income Data We develop our measure of ex-ante pandemic median household income using the latest [4] American Community Survey (ACS)âs ZCTA-code level median income data, which are the 2015-2019 5-year estimates [5]. The multiyear estimates are also used by other studies tracking the economics actives during COVID-19[6]. According to the United States Census Bureau, the multiyear estimates require additional consideration than single year estimates, and are therefore with increased statistical reliability, particularly for small geographic areas and small population subgroups. In the case of ACS 2015-2019 5-year estimates, the period is 5 calendar years from January 2015 through December 2019.

[3] The data and detailed descriptions for the data are available at https://www.realtor.com/research/data/.

[4] As of January 2022

[5] Detailed descriptions for the data are available at https://www.census.gov/data/developers/data-sets/acs-5year.html

[6] Other studies include Chetty et al (2020) and Zhao (2020)

Rates Data To account for the macroeconomics background, two sets of rates data are employed. First, we use the monthly mortgage rate data from the Primary Mortgage Market Survey, which is a widely used source provided by the Federal Home Loan Mortgage Corporation. For conventional purposes, the 30-year fixed-rate mortgages rates are used as the representatives. The 30-year fixed-rate mortgages are the most common product type in the US, according to statistics from National Mortgage Database (NMDB) aggregate data [7] and the New York Fed Consumer Credit Panel (CCP) data[8]. Secondly, we use the daily national data on effective federal funds rate from the Federal Reserve Bank of New York [9] and average the data to a monthly frequency. Both the mortgages rates data and the EFFR data are time-series data covering 37 months from January 2019 to January 2022.

For the purpose of matching the aforementioned datasets and supplementing additional geographical information, three additional crosswalk datasets are incorporated. Specifically, the block groups in ACS data are identified as ZIP Code Tabulation Areas (ZCTAs), which are created by the U.S. Census Bureau and are generalized representations of ZIP Codes that have been assigned to census blocks [10]. According to the United States Census Bureau, the most frequent occurring Zip code in an area was taken in creating the ZCTAs, which in most instances the ZCTA code is the same as the ZIP code. In this research, we run a crosswalk programming between ZCTA and Zip to merge income data with housing data, and 5 blocks are dropped due to failure in matching.

[7] Detailed descriptions for the data are available at https://www.fhfa.gov/DataTools/Downloads/Pages/National-Mortgage-Database-Aggregate-Data.aspx

[8] Detailed descriptions for the data are available at https://www.newyorkfed.org/microeconomics/hhdc/background

[9] Detailed descriptions for the data are available at https://www.newyorkfed.org/markets/reference-rates/effr

[10] Detailed descriptions for the data are available at https://www.census.gov/programs-surveys/geography/guidance/geo-areas/zctas.html

2.2 Variables, Analysis Samples, and Summary Statistics

2.2.1 Key Variables Specification

Demand Score We define the primary analysis sample beginning with housing demand measured as demand score at the ZIP-by-month level. Provided by realor.com, the demand score is an index representing a zip code listing page " views per property " *ranking* compared to other zip codes. Zhao (Zhao, 2020) also adopts such measure of housing demand to disentangle demand from other housing price drivers. For this research, we focus on the cross-sectional relative change and thus adopt such measurement as a suitable indicator for housing demand.

To study the heterogeneous housing demands responses to COVID-19 pandemic among different income groups, we exploit ex-ante pandemic median household income to interact with a set of observation window.

Median Household Income On the income side, two major concerns are incorporated. First, to ensure estimates are not biased by unparalleled geographical coverage, we use *household* [11] as the decision-making unit in residential housing market. Households, as the unit of analysis, embed more residential and dwelling information than family. Second, we stick to the *ex-ante pandemic income level* to minimize endogeneity issues in certain unobserved factors that may affect both housing demand and income distribution.

Groups of ZIP-codes by Income Based on the value of pre-pandemic median household income, we group our sample into four economic groups. The low-income zip codes are characterized by median household income less than \$52,200. The middle-income zip codes are characterized by median household income greater than \$52,200 while less than \$156,600. The upper-middle-income zip codes are characterized by median household income

[11] According to United States Census Bureau, a household consists of all people who occupy a housing unit regardless of relationship. A household may consist of a person living alone or multiple unrelated individuals or families living together. https://www.census.gov/hhes/www/income/about/faqs.html

greater than \$156,600 while less than \$200,000. The high-income zip codes are characterized by median household income greater than \$200,000. We follow Pew Research [12]to set the economic class boundaries for the low-to-middle class and middle-to-upper class. We also account for the growing size of upper-middle class proposed by Rose (2016) and set a boundary for upper-middle-income class and high-income class.

Time Periods On the observation window side, we identify three time periods based on the CDC Museum COVID-19 Timeline [13] and Fed monetary policy responses timeline. Period I account for changes in housing markets from January 2019 to March 2020; Period II account for changes in housing markets from March 2020 to August 2020; Period III account for changes in housing markets from August 2020 to January 2022.

2.2.2 Summary Statistics

Table 1 collects summary statistics for our sample before cleansing. We notice the existence of extreme outliers for major housing markets indicators, as the maximum of year-on-year growth rate of demand scores could be as high as 8799 percent. We therefore conduct four steps to filter outliers and null values.

Null observations Filter We exclude observations with zero value of median listing price per square foot, and 7 such observations are dropped.

Demand-side Filter We exclude observations with yearly demand score growth greater than five times. A total of 1406 (0.3 %) of such observations are dropped. These dropped observations are disproportionally distributed across months (see Figure 10 upper panel) and concentrated on months starting from August 2020. We find that the observations with a two to five times yearly demand score growth also displays the same distribution pattern

[12]The study defines middle-income Americans as those whose annual household income is two-thirds to double the national median (adjusted for local cost of living and household size), https://www.pewresearch.org/fact-tank/2020/07/23/are-you-in-the-american-middle-class/

[13]Detailed descriptions are available at https://www.cdc.gov/museum/timeline/covid19.html

across months (see Figure 10 lower panel). The two panels combined indicate that the filtering is conducted without causing obvious selection bias.

Supply-side Filter to ensure the treatment for supply is consistent with the treatment for demand, we conduct three sub-steps. First, We exclude observations with yearly total listing count (a measure of housing supply) growth greater than five times. A total of 53 of such observations are dropped. The distributional pattern of dropped observations is plotted in Figure 11. Second, we exclude observations with yearly median listing price per Sq-ft (a measure of housing price) growth greater than five times. A total of 95 of such observations are dropped. The distributional pattern of dropped observations is plotted in Figure 12. Third, we exclude observations with yearly median square feet (a measure of housing size) growth greater than five times. A total of 44 of such observations are dropped. The distributional pattern of dropped observations is plotted in Figure 13.

Missing Values Imputation we seasonally decomposes ZIP-code level monthly demand score and perform imputation on missing values accounting for both seasonal and deseasonalized components. Then, we generate the yearly growth rate of demand score at the ZIP-by-month level.

Table 2 collects summary statistics for our analysis sample after cleaning. The final sample contains 419433 ZIP-months for 11426 ZIPs across 1425 counties and 47 states.

Table 3 displays the even distribution of observations across months (37 months, 2.7 % per month), indicating the minimized sample selection bias towards any particular month.

2.3 Empirical Approach

Our empirical strategy exploits cross-sectional variation across ZIP-codes in ex-ante pandemic median household income to isolate the effect of the COVID-19 pandemic from aggregate macroeconomic shocks.

Table 1: Summary Statistics before Cleaning

Variable	Unit	N	Mean	Min	Median	Max	SD
Time Period I	NA	159, 964	NA	201, 901	NA	202, 002	NA
Time Period II	NA	68, 556	NA	202, 003	NA	202, 008	NA
Time Period III	NA	194, 242	NA	202, 009	NA	202, 201	NA
median_square_feet	foot	421, 038	7113	50	1900	2, 147, 483, 647	3309549
median_square_feet_mm	percent	420, 551	214	-100	0	89, 740, 128	138381
median_square_feet_yy	percent	419, 318	361	-99	-1	151, 124, 717	233380
median_listing_price_per_square_foot	$	421, 038	207	0	158	3, 500	179
median_listing_price_per_square_foot_mm	percent	420, 551	1	-99	0	7, 269	16
median_listing_price_per_square_foot_yy	percent	419, 318	10	-99	7	7, 462	30
total_listing_count	NA	422, 762	109	5	75	2, 878	113
total_listing_count_mm	percent	422, 762	-1	-82	-2	467	15
total_listing_count_yy	percent	422, 760	-6	-90	-11	1, 800	36
demand_score	NA	422, 762	46	0	45	99	26
demand_score_mm	percent	422, 762	2	-95	0	4, 925	27
demand_score_yy	percent	422, 762	12	-99	-1	8, 799	82
30Yr Fixed Mtg Rate	percent	422, 762	3	3	3	4	0
MedianFamilyIncome	$	420, 949	83659	19, 290	75513	249, 931	33912
MedianHouseholdIncome	$	422, 170	68974	17, 248	61718	248, 243	29170

Table 2: Summary Statistics after Cleaning

Variable	Unit	N	Mean	Min	Median	Max	SD
Time Period I	NA	158, 795	NA	201, 901	NA	202, 002	NA
Time Period II	NA	68, 134	NA	202, 003	NA	202, 008	NA
Time Period III	NA	192, 504	NA	202, 009	NA	202, 201	NA
median_square_feet	foot	419, 433	2010	50	1900	43, 124	702
median_square_feet_mm	percent	418, 954	0	-100	0	2, 410	11
median_square_feet_yy	percent	417, 717	0	-99	-1	496	17
median_listing_price_per_square_foot	$	419, 433	207	1	158	3, 500	179
median_listing_price_per_square_foot_mm	percent	418, 954	1	-99	0	7, 269	15
median_listing_price_per_square_foot_yy	percent	417, 717	10	-99	7	497	18
total_listing_count	NA	419, 433	109	5	76	2, 878	113
total_listing_count_mm	percent	419, 433	-1	-82	-1	467	15
total_listing_count_yy	percent	419, 431	-6	-90	-11	500	35
demand_score	NA	419, 433	46	0	45	99	26
demand_score_mm	percent	419, 433	2	-95	0	1, 302	25
demand_score_yy	percent	419, 433	9	-99	-2	500	60
30Yr Fixed Mtg Rate	percent	419, 433	3	3	3	4	0
MedianFamilyIncome	$	417, 639	83696	19, 290	75552	249, 931	33899
MedianHouseholdIncome	$	418, 858	69012	17, 248	61756	248, 243	29156

Table 3: Number of Observations across All Months (after Cleaning)

Month	Frequency	Percent	Cumulative
201901	11,296	2.700	2.7
201902	11,296	2.700	5.4
201903	11,270	2.700	8.1
201904	11,299	2.700	10.8
201905	11,313	2.700	13.5
201906	11,340	2.700	16.2
201907	11,358	2.700	18.9
201908	11,340	2.700	21.6
201909	11,400	2.700	24.3
201910	11,404	2.700	27
201911	11,378	2.700	29.7
201912	11,365	2.700	32.4
202001	11,371	2.700	35.1
202002	11,365	2.700	37.8
202003	11,361	2.700	40.5
202004	11,368	2.700	43.2
202005	11,365	2.700	45.9
202006	11,362	2.700	48.6
202007	11,356	2.700	51.3
202008	11,322	2.700	54
202009	11,310	2.700	56.7
202010	11,324	2.700	59.4
202011	11,323	2.700	62.1
202012	11,299	2.700	64.8
202101	11,313	2.700	67.5
202102	11,299	2.700	70.2
202103	11,295	2.700	72.9
202104	11,282	2.700	75.6
202105	11,322	2.700	78.3
202106	11,335	2.700	81
202107	11,343	2.700	83.7
202108	11,339	2.700	86.4
202109	11,343	2.700	89.1
202110	11,361	2.700	91.8
202111	11,346	2.700	94.5
202112	11,344	2.700	97.2
202201	11,326	2.700	99.9
Total	419,433	99.900	

We begin by estimating the differential response of housing demand by income groups to COVID-19 shocks using the following baseline regression:

$$\frac{\Delta D_{i,y,m}}{D_{i,y-1,m}} = \beta_0 + Income_i \times Period_{y,m} + \epsilon \tag{1}$$

For ZIP-code i in year y month m, $D_{i,y,m}$ denotes the monthly average demand score. $D_{i,y-1,m}$ denotes its monthly average demand score in the same month of the previous year. The left-hand side variable of equation **??** represents its demand score yearly growth.

$Income_i$ is a vector of income-group dummies, referring to the income group attribute of ZIP-code i. The income-groups are defined as low-income group, middle-income group, upper-middle-income group, and high-income group.

$Period_{y,m}$ is a vector of time-period dummies, referring to the period attribute of month

m. The time periods are defined as Period I (January 2019 to March 2020), Period II (March 2020 to August 2020), and Period III (August 2020 to January 2022).

3 Heterogeneous Demand Responses by Income

3.1 Distributional Pattern of Housing Demand

3.1.1 Baseline Model Results

Column (1) in Table 6 presents regression results from baseline model 1, which includes only the interaction of income-group attribute of ZIP-code i and time period attribute of month m.

Our specification allows us to estimate the average yearly demand score growth with the results (Table 4). The average pre-pandemic yearly demand score growth for each income-groups (low to high) is shown in row 1. The average yearly demand score growth for each income-groups (low to high) in the first six months of pandemic is shown in row 2. The average yearly demand score growth for each income-groups (low to high) afterwards is shown in row 3.

Table 4: Average Demand Score Yearly Growth across Income Groups from Baseline Model

Period	Low	Middle	Upper_Middle	High
Time Period I	14.510	0.075	-7.356	-10.484
Time Period II	14.446	8.126	7.300	16.300
Time Period III	18.924	9.858	-6.667	7.628

The pattern is also shown in Figure 3.1.1, which plots the estimates of average demand score yearly growth by income group through time. We see housing demand as a whole, proxied by demand score yearly growth, has been rising during the pandemic period, especially for upper-middle-income ZIPs and high-income ZIPs.

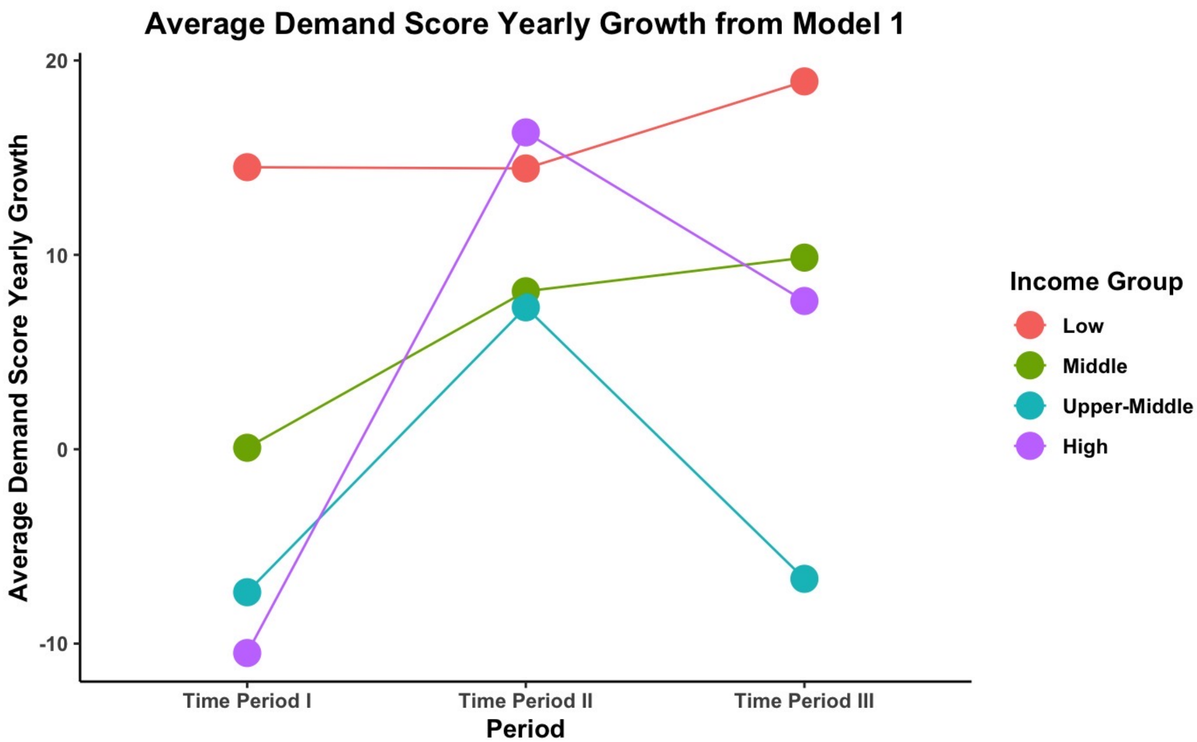

Figure 2: Average Demand Score Yearly Growth from Baseline Model

3.1.2 Accounting for Housing Supply & Housing Price

One concern about our baseline model is: the changes in housing demand distribution pattern may be driven by ZIP-code level housing supply composition changes, which include the changes in **median house size** [14], in **total active listing**, and in **median listing price**. We notice the importance of mitigating the impact of the change in housing supply composition.

To empirically address the concern, we implement the composition effect variable $C_{i,y,m}$ and describe it in equation 2.

[14]Measured as median square feet of houses

$$C_{i,y,m} = Sqft\ Price_{i,y,m} + Size_{i,y,m} + Active\ Listing_{i,y,m} \tag{2}$$

$Sqft\ Price_{i,y,m}$ denotes the ZIP-code level median listing price per square foot. $Size_{i,y,m}$ denotes the ZIP-code level median house size (square feet). $Active\ Listing_{i,y,m}$ denotes the ZIP-code level total active listings count.

Based on design in equation 1 and equation 2, we further include control on **monthly average mortgages rates** denoted by $r_{y,m}$ and propose the regression 3 for Model 2:

$$\frac{\Delta D_{i,y,m}}{D_{i,y-1,m}} = \beta_0 + Income_i \times Period_{y,m} + C_{i,y,m} + r_{y,m} + \epsilon \tag{3}$$

Column (2) in Table 6 presents regression results from the model with housing supply composition effect, as specified in 3. Our specification allows us to estimate the average yearly demand score growth with the results (Table 5). The average pre-pandemic yearly demand score growth for each income-groups (low to high) is shown in row 1. The average yearly demand score growth for each income-groups (low to high) in the first six months of the pandemic is shown in row 2. The average yearly demand score growth for each income-groups (low to high) afterwards is shown in row 3.

The results indicate that the average yearly growth of demand score for upper-middle income ZIPs increased *11.178 %* in the first six months of the pandemic, which indicates a *370 %* increase rate from its pre-pandemic level.

For high-income ZIPs, the average yearly growth of demand score increase *22.711 %* in the first six months of pandemic and changed its previous negative trend to positive yearly growth as high as 22.059%.

We visualize the pattern in Figure 3.1.2, which plots the estimates of average demand score yearly growth by income through time. The increase in demand score yearly growth

Table 5: Average Demand Score Yearly Growth across Income Groups from Model 2

Period	Low	Middle	Upper_Middle	High
Time Period I	25.646	11.308	3.019	-0.652
Time Period II	22.164	16.004	14.197	22.059
Time Period III	26.104	17.867	0.813	13.198

of high-income ZIPs and upper-middle income ZIPs are quite strong in the first six months of pandemic.

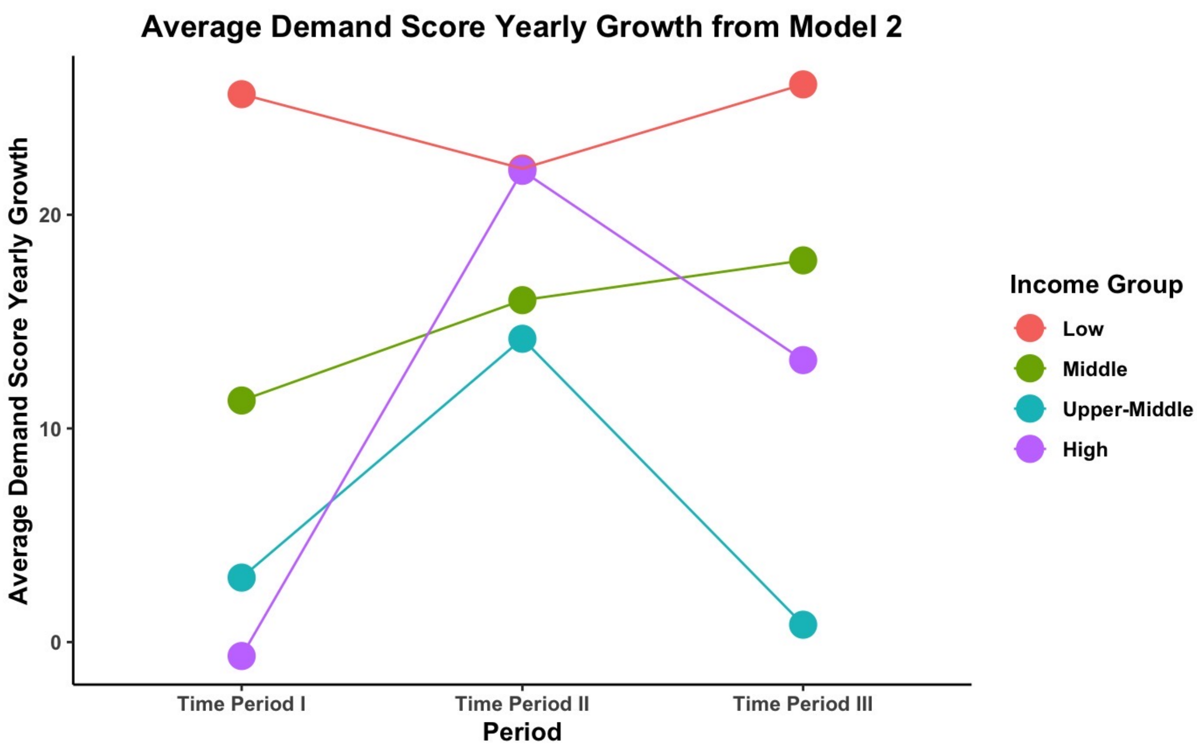

Figure 3: Average Demand Score Yearly Growth from Model 2

3.2 Robustness Check

Substantial variation in ex-ante pandemic income within counties and states allow us to pursue a research design that accounts for county-level and state-level effects. We therefore conduct the following robustness checks.

Table 6: Summary of Model 1-2

	Dependent variable:	
	demand_score_yy	
	(1)	(2)
PeriodII	−0.064	−3.482***
	(0.484)	(0.552)
PeriodIII	4.414***	0.458
	(0.358)	(0.511)
IncomeMiddle	−14.435***	−14.338***
	(0.323)	(0.332)
IncomeUpper-Middle	−21.866***	−22.627***
	(1.428)	(1.451)
IncomeHigh	−24.994***	−26.298***
	(2.723)	(2.733)
price_per_square		−0.033***
		(0.001)
median_square_feet		0.007***
		(0.0001)
total_listing_count		−0.009***
		(0.001)
‘30Yr Fixed Mtg Rate‘		−4.867***
		(0.392)
PeriodII:IncomeMiddle	8.116***	8.170***
	(0.590)	(0.585)
PeriodIII:IncomeMiddle	5.369***	6.093***
	(0.437)	(0.433)
PeriodII:IncomeUpper-Middle	14.720***	14.660***
	(2.608)	(2.586)
PeriodIII:IncomeUpper-Middle	−3.726*	−2.664
	(1.929)	(1.913)
PeriodII:IncomeHigh	26.848***	26.193***
	(4.979)	(4.937)
PeriodIII:IncomeHigh	13.697***	13.392***
	(3.677)	(3.646)
Constant	14.510***	25.646***
	(0.265)	(1.571)
Observations	418,858	418,858
R^2	0.012	0.029
Adjusted R^2	0.012	0.029
Residual Std. Error	59.986 (df = 418846)	59.472 (df = 418842)
F Statistic	455.512*** (df = 11; 418846)	824.420*** (df = 15; 418842)
Note:		*p<0.1; **p<0.05; ***p<0.01

3.2.1 Accounting for State-level Effect

With variable $State_i$ denoting the state attribute of ZIP-code i, regression 4 is designed to control state-level unobserved factors that potentially affect housing demand patterns.

$$\frac{\Delta D_{i,y,m}}{D_{i,y-1,m}} = \beta_0 + Income_i \times Period_{y,m} + C_{i,y,m} + r_{y,m} + State_i + \epsilon \tag{4}$$

Table 15 presents regression results from model 3 as specified in 4. Our specification allows us to estimate the average yearly demand score growth with the results (Table 7). The average pre-pandemic yearly demand score growth for each income-groups (low to high) is shown in row 1. The average yearly demand score growth for each income-groups (low to high) in the first six months of pandemic is shown in row 2. The average yearly demand score growth for each income-groups (low to high) afterwards is shown in row 3.

The results are also shown in Figure 4, which plots the estimates of average demand score yearly growth by income group through time.

The strong increase in demand score yearly growth of high-income ZIPs and upper-middle income ZIPs remain robust. Such results rule out the possibility that the pattern is driven by unobserved State-level effect.

Table 7: Robustness Check Results Summary

period	Low	Middle	Upper_Middle	High
Time Period I	69.146	58.398	53.808	50.490
Time Period II	65.454	62.901	64.797	73.098
Time Period III	69.174	64.368	50.988	63.882

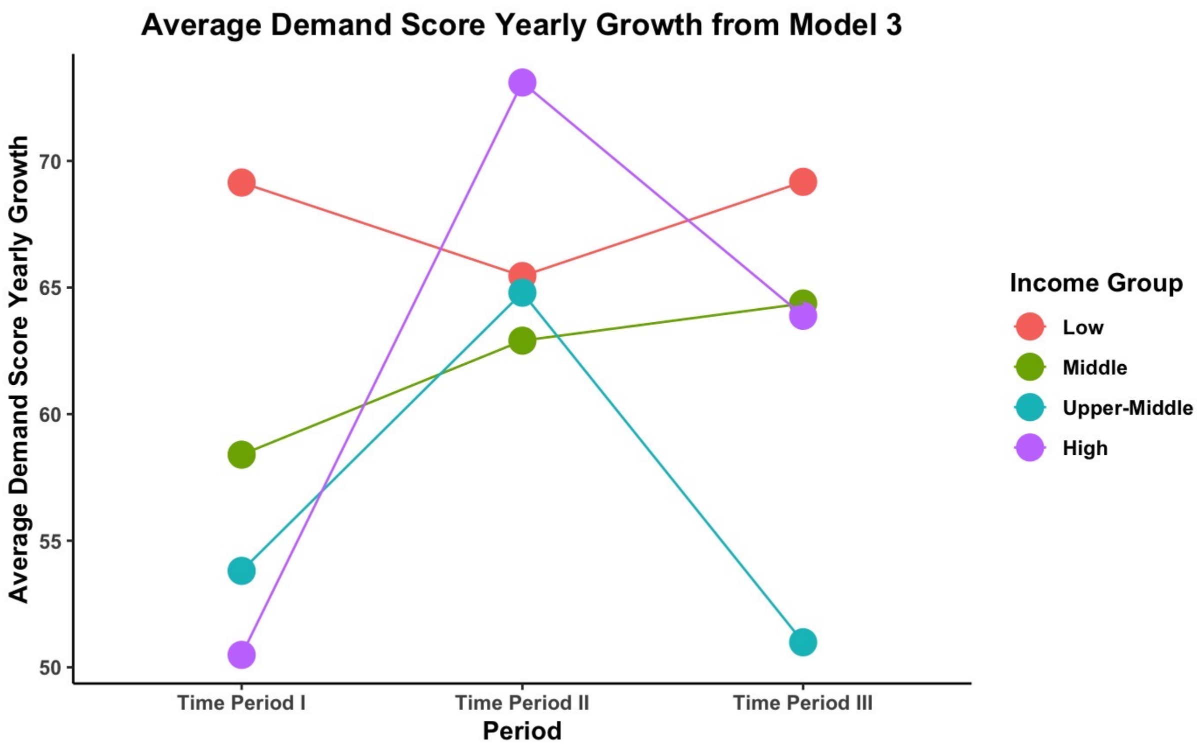

Figure 4: Average Demand Score Yearly Growth from Robustness Check on State-level

3.2.2 Accounting for County-level Effect

With variable $County_i$ denoting the county attribute of ZIP-code i, regression 5 is designed to control county-level unobserved factors that potentially affect housing demand pattern across income groups.

$$\frac{\Delta D_{i,y,m}}{D_{i,y-1,m}} = \beta_0 + Income_i \times Period_{y,m} + C_{i,y,m} + r_{y,m} + County_i + \epsilon \tag{5}$$

Table 8 presents regression results from model 4 as specified in 5. Our specification allows us to estimate the average yearly demand score growth with the results. The average pre-pandemic yearly demand score growth for each income-groups (low to high) is shown in row 1. The average yearly demand score growth for each income-groups (low to high) in the first six months of pandemic is shown in row 2. The average yearly demand score growth for each income-groups (low to high) afterwards is shown in row 3.

The results are also shown in Figure 5, which plots the estimates of average demand score yearly growth by income group through time.

The strong increase in demand score yearly growth of high-income ZIPs and upper-middle income ZIPs remain robust. Such results rule out the possibility that the pattern is driven by unobserved County-level effect.

Table 8: Robustness Check Results

period	Low	Middle	Upper_Middle	High
Time Period I	42.426	35.729	36.447	29.368
Time Period II	38.289	39.752	47.005	51.569
Time Period III	41.530	40.402	32.233	40.986

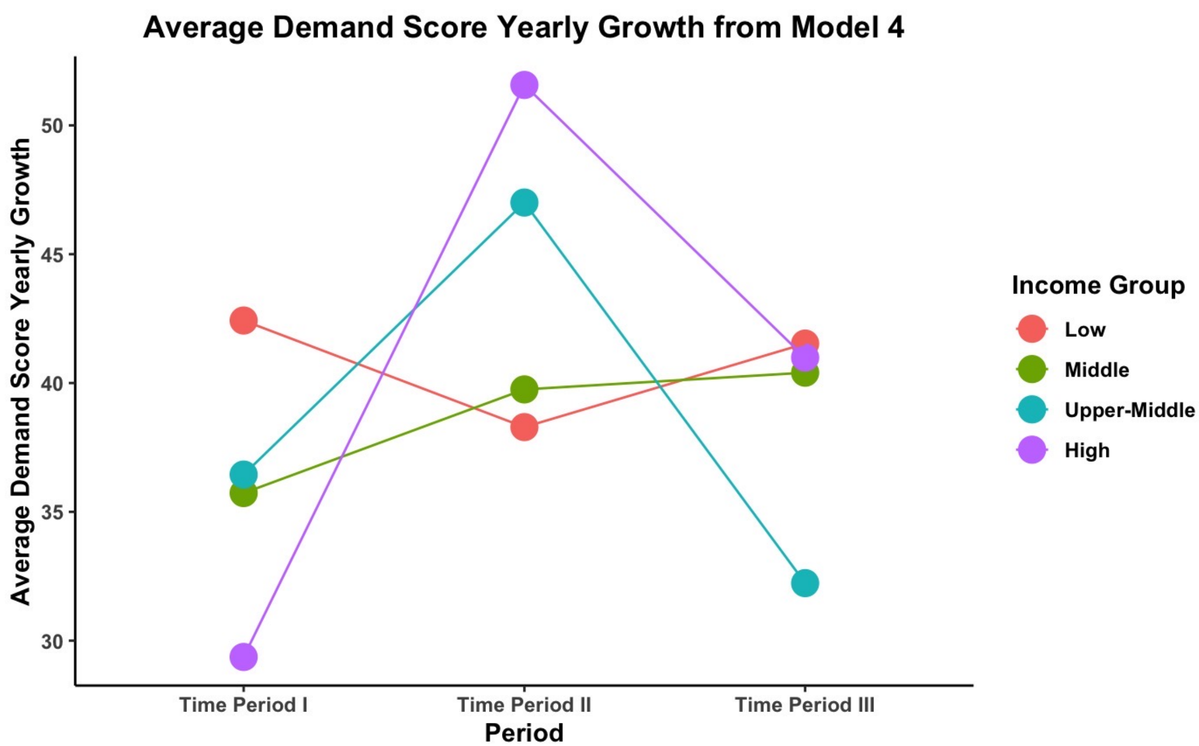

Figure 5: Average Demand Score Yearly Growth from Robustness Check on County-level

3.3 Results Summary

Based on the results from baseline regression 1 and three following robustness-checking regressions 3 4 5, we draw the following conclusion: during pandemic, the increase in the housing demand yearly growth is particularly strong in the upper-middle-income ZIPs and high-income ZIPs. The results remain robust after controlling for the housing supply effect, the State-level effect, and the County-level effect.

4 Roles of Housing Prices and Mortgages Rates

Motivated by the results in Section 3, we unfold the second step of our empirical analysis and conduct a closer examination on the drivers of demand increase in high income ZIPs.

We pose two hypotheses through the speculation channel:

Housing Price Speculation Hypothesis The surged housing demand yearly increase during the pandemic in upper-middle-income ZIPs and high-income ZIPs is driven by *fast-growing housing prices.*

Rates-Incentive Hypothesis The surged housing demand yearly increase during pandemic in upper-middle-income ZIPs and high-income ZIPs is driven by *ultra-low mortgages rates.*

4.1 The Effect of Housing Price on Housing Demand

With a focus on the Housing Price Speculation Hypothesis, we first test the demand responses to housing price changes within income groups and observe how households' behaviors changed through time.

We estimate the following specification to explore the heterogeneity by period:

$$\frac{\Delta D^G_{i,y,m}}{D^G_{i,y-1,m}} = \beta_0 + Sqft\ Price^G_{i,y,m} \times Period_{y,m} + C^{G'}_{i,y,m} + r_{y,m} + \epsilon \tag{6}$$

G refers to the income-group attribute of ZIP-code i, whereas $C^{G'}_{i,y,m}$ combines $Size^G_{i,y,m}$ and $Active\ Listing^G_{i,y,m}$.

Controlling for housing supply and mortgages rates, we conduct four regressions within each income group with results in Table 16, Table 17, Table 18, and Table 19. The combined results are presented in Table 9.

Table 9: Summary of Models Testing Housing Price Speculation Hypothesis

	Dependent variable:			
	demand_score_yy			
	Low	Middle	Upper-Middle	High
	(1)	(2)	(3)	(4)
PeriodII	-4.305^{***}	-0.523	30.982^{***}	55.970^{***}
	(1.078)	(0.583)	(3.850)	(7.507)
PeriodIII	7.704^{***}	3.961^{***}	20.083^{***}	16.684^{**}
	(1.023)	(0.565)	(3.684)	(7.286)
price_per_square	-0.083^{***}	-0.031^{***}	-0.011^{***}	-0.018^{***}
	(0.003)	(0.001)	(0.003)	(0.005)
'30Yr Fixed Mtg Rate'	0.112	-7.281^{***}	7.995^{***}	15.855^{***}
	(0.784)	(0.447)	(2.790)	(5.476)
median_square_feet	0.017^{***}	0.006^{***}	0.003^{***}	0.005^{***}
	(0.0004)	(0.0002)	(0.0005)	(0.001)
total_listing_count	-0.031^{***}	-0.001	-0.020^{**}	-0.032^{*}
	(0.002)	(0.001)	(0.008)	(0.017)
PeriodII:price_per_square	0.032^{***}	0.016^{***}	-0.023^{***}	-0.033^{***}
	(0.006)	(0.002)	(0.006)	(0.009)
PeriodIII:price_per_square	-0.013^{***}	0.002	-0.023^{***}	0.023^{***}
	(0.004)	(0.001)	(0.004)	(0.007)
Constant	-1.206	22.156^{***}	-40.721^{***}	-76.663^{***}
	(3.193)	(1.798)	(11.220)	(22.485)
Observations	135,314	277,425	4,825	1,294
R^2	0.032	0.023	0.074	0.125
Adjusted R^2	0.032	0.023	0.073	0.120
Residual Std. Error	67.524 (df = 135305)	55.105 (df = 277416)	45.306 (df = 4816)	46.050 (df = 1285)
F Statistic	567.847^{***} (df = 8; 135305)	824.459^{***} (df = 8; 277416)	48.174^{***} (df = 8; 4816)	22.996^{***} (df = 8; 1285)
Note:				*p<0.1; **p<0.05; ***p<0.01

Our specification allows us to estimate the slopes, which represent housing demand's **sensitivity** to housing prices. We present the summarized model results interpretation in Table 10.

The average pre-pandemic sensitivity to prices for each income-groups (low to high) is shown in row 1. The average sensitivity to prices for each income-groups (low to high) in the first six months of pandemic is shown in row 2. The average sensitivity to prices for each income-groups (low to high) afterwards is shown in row 3.

For upper-middle income ZIPs, the absolute value of sensitivity rises from 0.011 to 0.034 during pandemic, meaning one unit of price increase would cause a larger reduction in household demand.

For high-income ZIPs, the absolute value of sensitivity also raises from 0.018 to 0.051, indicating the same high-price-averse housing demand preference.

The results constitute evidence against the hypothesis that fast-growing housing prices drive up high-income ZIPs' housing demand.

Table 10: Estimated Sensitivity to Housing Prices

Period	Low	Middle	Upper_Middle	High
Time Period I	-0.083	-0.031	-0.011	-0.018
Time Period II	-0.051	-0.015	-0.034	-0.051
Time Period III	-0.096	-0.029	-0.034	0.005

4.2 The Effect of Mortgages Rates on Housing Demand

We now turn to the impact of low mortgages rates on the high-income ZIPs' housing demand increase.

We test the demand responses to mortgages rates change within income groups and observe how households behaviors changed through time. We estimate the following specification to explore the effect of mortgages rate $r_{y,m}$ by period:

$$\frac{\Delta D^G_{i,y,m}}{D^G_{i,y-1,m}} = \beta_0 + r_{y,m} \times Period_{y,m} + C^G_{i,y,m} + \epsilon \tag{7}$$

G also refers to the income-group attribute of ZIP-code i, whereas $C^G_{i,y,m}$ combines the housing price $Sqft\ Price_{i,y,m}$, the housing size $Size^G_{i,y,m}$ and the total listing $Active\ Listing^G_{i,y,m}$.

Controlling for housing supply factors and housing prices, we conduct four regressions within each income group with results displayed in Table 20, Table 21, Table 22, and Table 23. The combined results are presented in Table 11.

Table 11: Summary of Models Testing Rates-Incentive Hypothesis

	Dependent variable:			
	demand_score_yy			
	Low	Middle	Upper-Middle	High
	(1)	(2)	(3)	(4)
PeriodII	32.958***	−13.018**	32.740	77.191
	(9.299)	(5.297)	(32.691)	(65.090)
PeriodIII	41.746***	−51.638***	−226.118***	−193.336***
	(5.883)	(3.350)	(20.690)	(41.119)
‘30Yr Fixed Mtg Rate‘	3.708***	−12.258***	−10.916***	−0.477
	(0.972)	(0.554)	(3.416)	(6.798)
price_per_square	−0.084***	−0.028***	−0.027***	−0.013***
	(0.002)	(0.001)	(0.002)	(0.003)
median_square_feet	0.017***	0.006***	0.003***	0.005***
	(0.0004)	(0.0002)	(0.0005)	(0.001)
total_listing_count	−0.031***	−0.001	−0.017**	−0.016
	(0.002)	(0.001)	(0.008)	(0.017)
PeriodII:‘30Yr Fixed Mtg Rate‘	−9.598***	3.975**	−8.071	−16.139
	(2.835)	(1.615)	(9.968)	(19.850)
PeriodIII:‘30Yr Fixed Mtg Rate‘	−11.046***	17.431***	73.787***	71.304***
	(1.810)	(1.031)	(6.370)	(12.667)
Constant	−14.888***	40.751***	40.350***	−19.064
	(3.871)	(2.191)	(13.537)	(27.169)
Observations	135,314	277,425	4,825	1,294
R^2	0.032	0.024	0.095	0.120
Adjusted R^2	0.032	0.024	0.093	0.115
Residual Std. Error	67.530 (df = 135305)	55.086 (df = 277416)	44.803 (df = 4816)	46.182 (df = 1285)
F Statistic	564.990*** (df = 8; 135305)	848.973*** (df = 8; 277416)	62.855*** (df = 8; 4816)	21.948*** (df = 8; 1285)
Note:				*p<0.1; **p<0.05; ***p<0.01

Our specification allows us to estimate the slopes, which represent housing demand's **sensitivity** to mortgage rates. We present the summarized model results interpretation in Table 12.

The average pre-pandemic sensitivity to mortgage rates for each income-groups (low to

Table 12: Estimated Sensitivity to Mortgage Rates

Period	Low	Middle	Upper_Middle	High
Time Period I	3.708	-12.258	-10.916	-0.477
Time Period II	-5.890	-8.283	-18.987	-16.616
Time Period III	-7.338	5.173	62.871	70.827

high) is shown in row 1. The average sensitivity to mortgage rates for each income-groups (low to high) in the first six months of pandemic is shown in row 2. The average sensitivity to mortgage rates for each income-groups (low to high) afterwards is shown in row 3.

The sensitivity changes for upper-middle income ZIPs and high-income ZIPs are plotted in Figure 6 and Figure 7.

For upper-middle-income ZIPs, as shown in 6, the absolute value of slopes increased from 10 to 18 from pre-epidemic level, meaning that one unit decrease in mortgage rate would cause a lager increase in housing demand. The results constitute evidence to support our hypothesis that mortgage rates serve as strong incentives for households.

For high-income ZIPs, as shown in 7, the changes in sensitivity become more obvious. The absolute value of slopes increased **33** times during pandemic, from -0.477 to 16.616, meaning that the high-income ZIPs become much more sensitive to mortgage rates change during pandemic. The results further constitute evidence to support our hypothesis that mortgage rates serve as strong incentives for households.

In sum, the existing evidence provides suggestive evidence that housing demand of high-income ZIPs and upper-middle-income ZIPs tend to be more sensitive to changes in mortgages rates, which provides explanations for the observed pattern in section 3.

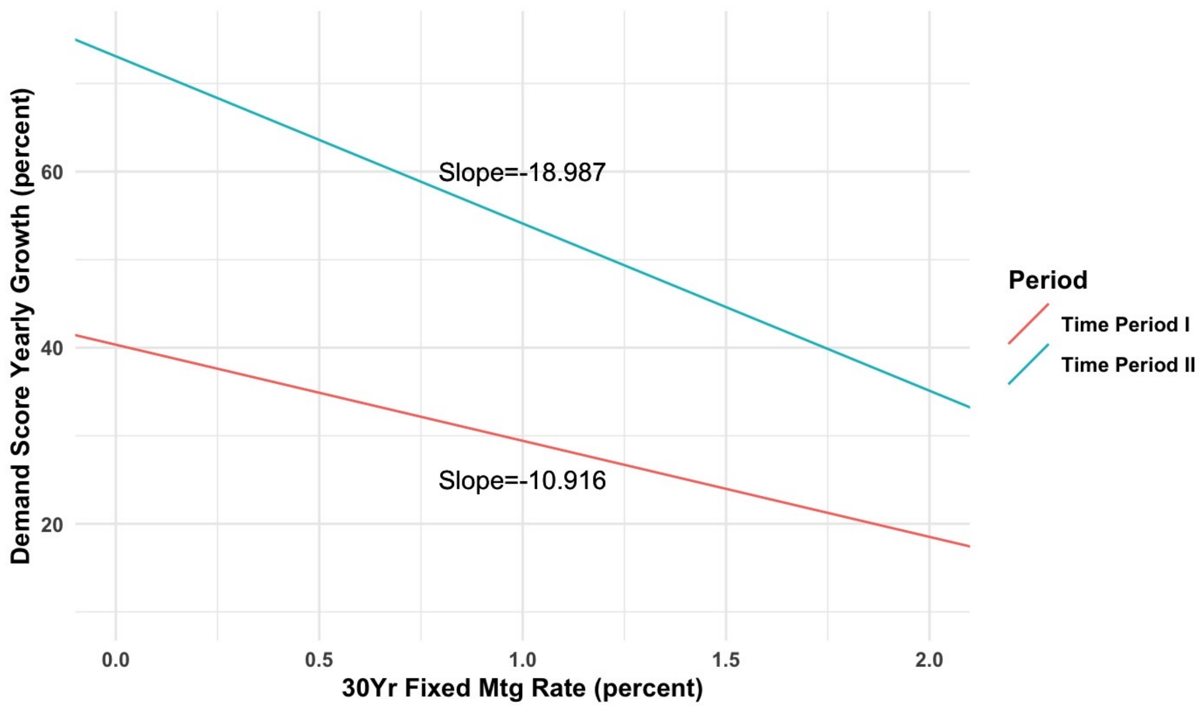

Figure 6: Estimated Sensitivity to Mortgage Rates of Upper-middle-income ZIPs

5 Conclusion

This paper asks whether COVID-19 pandemic has altered the distributional pattern of housing demand among income groups. With the ex-ante pandemic median household income, we find that the pandemic had a disparate impact on housing demand of ZIP-codes with different income levels. We document that the pandemic caused a meaningful increase in housing demand growth rates for high-income ZIPs and upper-middle-income ZIPs across the country, while similar increase trends in growth rates could not be observed from low-income ZIPs and middle-income ZIPs.

The altered distributional pattern of housing demand holds true even after controlling for variation in ZIP-code level housing supply factors and variation in state-level & county-level effects.

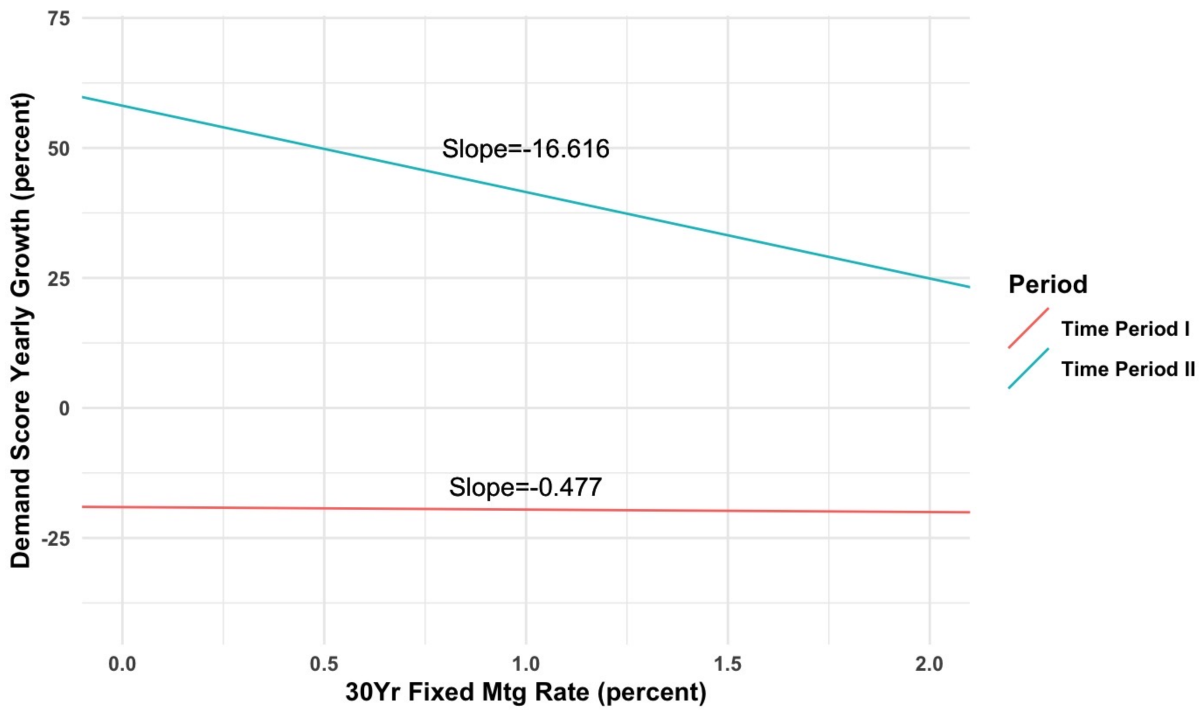

Figure 7: Estimated Sensitivity to Mortgage Rates of High-income ZIPs

We also document that the ultra-low mortgage rates during the pandemic proved effective at spurring housing demands at high-income ZIPs and upper-middle-income ZIPs. However, the evidence fails to support that the surged housing demand yearly growth is driven by fast-growing pricing. The results suggest that the reduced-cost channel dominates the increased-potential-gain channel in the speculative investment mechanism.

As the most up-to-date research on the housing market during pandemic, this paper also contributes to the literature about the effects of health crises on housing markets & general economy, the evolution of wealth inequality during the pandemic, and the effects of monetary easing on housing markets.

This paper calls for further studies to closely examine the aforementioned findings. Specifically, formally testing the Rates-Incentive Hypothesis is beyond the scope of this paper. We think it is a meaningful avenue to incorporate ZIP-code level tenor-weighted mortgage rates to consolidate the empirical heterogeneity across income groups. We leave this to future research.

6 Appendix: Figures & Tables

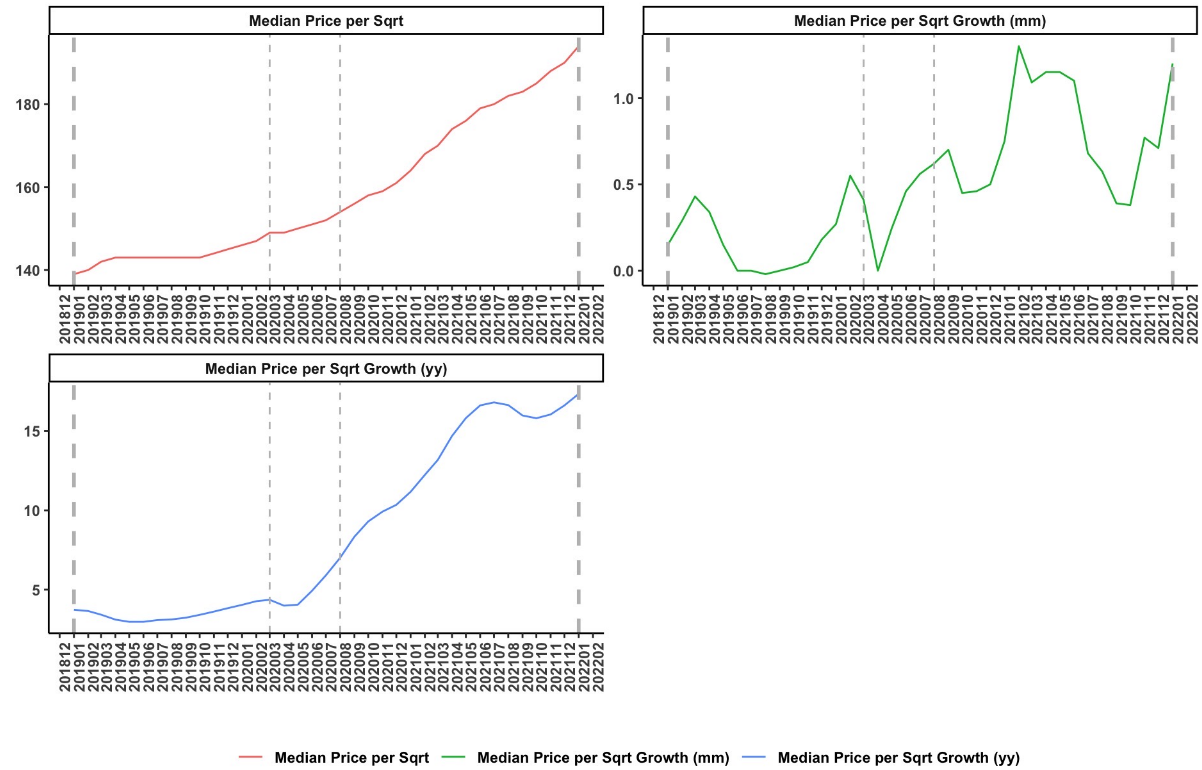

Figure 8: Housing Price from January 2019 to January 2022

Table 13: Summary of Baseline Model

term	estimate	std.error	statistic	p.value
(Intercept)	14.510	0.265	54.773	0
PeriodII	-0.064	0.484	-0.133	0.894
PeriodIII	4.414	0.358	12.331	0
IncomeMiddle	-14.435	0.323	-44.663	0
IncomeUpper-Middle	-21.866	1.428	-15.314	0
IncomeHigh	-24.994	2.723	-9.179	0
PeriodII:IncomeMiddle	8.116	0.590	13.757	0
PeriodIII:IncomeMiddle	5.369	0.437	12.295	0
PeriodII:IncomeUpper-Middle	14.720	2.608	5.643	0.00000
PeriodIII:IncomeUpper-Middle	-3.726	1.929	-1.931	0.053
PeriodII:IncomeHigh	26.848	4.979	5.392	0.00000
PeriodIII:IncomeHigh	13.697	3.677	3.725	0.0002

Table 14: Summary of Model 2

term	estimate	std.error	statistic	p.value
(Intercept)	25.646	1.571	16.320	0
PeriodII	-3.482	0.552	-6.313	0
PeriodIII	0.458	0.511	0.896	0.370
IncomeMiddle	-14.338	0.332	-43.125	0
IncomeUpper-Middle	-22.627	1.451	-15.594	0
IncomeHigh	-26.298	2.733	-9.623	0
price_per_square	-0.033	0.001	-58.867	0
median_square_feet	0.007	0.0001	51.881	0
total_listing_count	-0.009	0.001	-11.385	0
‘30Yr Fixed Mtg Rate‘	-4.867	0.392	-12.402	0
PeriodII:IncomeMiddle	8.170	0.585	13.968	0
PeriodIII:IncomeMiddle	6.093	0.433	14.067	0
PeriodII:IncomeUpper-Middle	14.660	2.586	5.669	0
PeriodIII:IncomeUpper-Middle	-2.664	1.913	-1.393	0.164
PeriodII:IncomeHigh	26.193	4.937	5.306	0.00000
PeriodIII:IncomeHigh	13.392	3.646	3.674	0.0002

Table 15: Summary of Robustness Check on State-level

term	estimate	std.error	statistic	p.value
(Intercept)	69.146	2.274	30.407	0
PeriodII	-3.692	0.544	-6.781	0
PeriodIII	0.034	0.505	0.067	0.947
IncomeMiddle	-10.742	0.336	-31.936	0
IncomeUpper-Middle	-15.332	1.441	-10.638	0
IncomeHigh	-18.650	2.707	-6.890	0
price_per_square	-0.031	0.001	-46.784	0
median_square_feet	0.006	0.0001	41.661	0
total_listing_count	-0.018	0.001	-19.700	0
‘30Yr Fixed Mtg Rate‘	-5.099	0.387	-13.163	0
stateAL	-19.227	1.791	-10.735	0
stateAR	-16.437	1.872	-8.778	0
stateAZ	-38.234	1.794	-21.311	0
stateCA	-42.378	1.708	-24.808	0
stateCO	-46.963	1.792	-26.206	0
stateCT	-44.750	1.812	-24.700	0
stateDC	-76.161	2.697	-28.241	0
stateDE	-38.108	2.206	-17.271	0
stateFL	-32.969	1.714	-19.237	0
stateGA	-37.345	1.753	-21.302	0
stateHI	-27.759	2.155	-12.880	0
stateIA	-49.755	1.876	-26.516	0
stateID	-43.087	2.049	-21.030	0
stateIL	-49.530	1.733	-28.585	0
stateIN	-52.044	1.801	-28.894	0
stateKS	-38.160	1.925	-19.824	0
stateKY	-42.814	1.858	-23.043	0
stateLA	-45.108	1.829	-24.662	0
stateMA	-46.614	1.783	-26.138	0
stateMD	-45.009	1.806	-24.918	0
stateME	-20.140	2.003	-10.057	0
stateMI	-48.287	1.738	-27.782	0
stateMN	-52.531	1.788	-29.377	0
stateMO	-38.031	1.784	-21.321	0
stateMS	-33.361	1.920	-17.375	0
stateMT	-7.127	2.111	-3.377	0.001
stateNC	-29.184	1.756	-16.619	0
stateND	-41.144	2.616	-15.725	0
stateNE	-60.390	2.086	-28.953	0
stateNH	-39.905	2.251	-17.731	0
stateNJ	-46.874	1.740	-26.945	0
stateNM	-27.425	2.054	-13.354	0
stateNV	-58.907	1.954	-30.141	0
stateNY	-50.298	1.713	-29.355	0
stateOH	-53.714	1.746	-30.763	0
stateOK	-33.179	1.861	-17.825	0
stateOR	-47.795	1.857	-25.739	0
statePA	-51.349	1.730	-29.686	0
stateRI	-40.067	2.238	-17.901	0
stateSC	-29.250	1.825	-16.030	0
stateSD	-42.613	2.359	-18.060	0
stateTN	-40.922	1.798	-22.766	0
stateTX	-47.989	1.706	-28.126	0
stateUT	-30.538	1.962	-15.563	0
stateVA	-34.439	1.757	-19.606	0
stateVT	-8.275	2.374	-3.486	0.0005
stateWA	-47.078	1.811	-25.996	0
stateWI	-33.732	1.792	-18.819	0
stateWV	-28.193	2.004	-14.069	0
stateWY	-8.928	2.338	-3.819	0.0001
PeriodII:IncomeMiddle	8.195	0.577	14.200	0
PeriodIII:IncomeMiddle	5.936	0.427	13.885	0
PeriodII:IncomeUpper-Middle	14.681	2.552	5.753	0
PeriodIII:IncomeUpper-Middle	-2.854	1.887	-1.512	0.131
PeriodII:IncomeHigh	26.300	4.872	5.399	0.00000
PeriodIII:IncomeHigh	13.358	3.598	3.713	0.0002

Table 16: Summary of Model 5

term	estimate	std.error	statistic	p.value
(Intercept)	-1.206	3.193	-0.378	0.706
PeriodII	-4.305	1.078	-3.993	0.0001
PeriodIII	7.704	1.023	7.530	0
price_per_square	-0.083	0.003	-25.558	0
‘30Yr Fixed Mtg Rate‘	0.112	0.784	0.143	0.886
median_square_feet	0.017	0.0004	39.951	0
total_listing_count	-0.031	0.002	-15.046	0
PeriodII:price_per_square	0.032	0.006	5.469	0.00000
PeriodIII:price_per_square	-0.013	0.004	-2.993	0.003

Table 17: Summary of Model 6

term	estimate	std.error	statistic	p.value
(Intercept)	22.156	1.798	12.324	0
PeriodII	-0.523	0.583	-0.896	0.370
PeriodIII	3.961	0.565	7.009	0
price_per_square	-0.031	0.001	-32.122	0
‘30Yr Fixed Mtg Rate‘	-7.281	0.447	-16.284	0
median_square_feet	0.006	0.0002	39.982	0
total_listing_count	-0.001	0.001	-1.298	0.194
PeriodII:price_per_square	0.016	0.002	9.375	0
PeriodIII:price_per_square	0.002	0.001	1.598	0.110

Table 18: Summary of Model 7

term	estimate	std.error	statistic	p.value
(Intercept)	-40.721	11.220	-3.629	0.0003
PeriodII	30.982	3.850	8.048	0
PeriodIII	20.083	3.684	5.452	0.00000
price_per_square	-0.011	0.003	-3.510	0.0005
‘30Yr Fixed Mtg Rate‘	7.995	2.790	2.866	0.004
median_square_feet	0.003	0.0005	5.987	0
total_listing_count	-0.020	0.008	-2.402	0.016
PeriodII:price_per_square	-0.023	0.006	-4.027	0.0001
PeriodIII:price_per_square	-0.023	0.004	-5.451	0.00000

Table 19: Summary of Model 8

term	estimate	std.error	statistic	p.value
(Intercept)	-76.663	22.485	-3.410	0.001
PeriodII	55.970	7.507	7.456	0
PeriodIII	16.684	7.286	2.290	0.022
price_per_square	-0.018	0.005	-3.545	0.0004
‘30Yr Fixed Mtg Rate‘	15.855	5.476	2.896	0.004
median_square_feet	0.005	0.001	4.734	0.00000
total_listing_count	-0.032	0.017	-1.840	0.066
PeriodII:price_per_square	-0.033	0.009	-3.627	0.0003
PeriodIII:price_per_square	0.023	0.007	3.521	0.0004

Table 20: Summary of Model 9

term	estimate	std.error	statistic	p.value
(Intercept)	-14.888	3.871	-3.846	0.0001
PeriodII	32.958	9.299	3.544	0.0004
PeriodIII	41.746	5.883	7.096	0
‘30Yr Fixed Mtg Rate‘	3.708	0.972	3.813	0.0001
price_per_square	-0.084	0.002	-44.051	0
median_square_feet	0.017	0.0004	39.811	0
total_listing_count	-0.031	0.002	-15.167	0
PeriodII:‘30Yr Fixed Mtg Rate‘	-9.598	2.835	-3.386	0.001
PeriodIII:‘30Yr Fixed Mtg Rate‘	-11.046	1.810	-6.101	0

Table 21: Summary of Model 10

term	estimate	std.error	statistic	p.value
(Intercept)	40.751	2.191	18.596	0
PeriodII	-13.018	5.297	-2.458	0.014
PeriodIII	-51.638	3.350	-15.415	0
‘30Yr Fixed Mtg Rate‘	-12.258	0.554	-22.107	0
price_per_square	-0.028	0.001	-48.945	0
median_square_feet	0.006	0.0002	39.935	0
total_listing_count	-0.001	0.001	-0.672	0.502
PeriodII:‘30Yr Fixed Mtg Rate‘	3.975	1.615	2.462	0.014
PeriodIII:‘30Yr Fixed Mtg Rate‘	17.431	1.031	16.911	0

Table 22: Summary of Model 11

term	estimate	std.error	statistic	p.value
(Intercept)	40.350	13.537	2.981	0.003
PeriodII	32.740	32.691	1.002	0.317
PeriodIII	-226.118	20.690	-10.929	0
‘30Yr Fixed Mtg Rate‘	-10.916	3.416	-3.195	0.001
price_per_square	-0.027	0.002	-12.887	0
median_square_feet	0.003	0.0005	5.538	0.00000
total_listing_count	-0.017	0.008	-2.124	0.034
PeriodII:‘30Yr Fixed Mtg Rate‘	-8.071	9.968	-0.810	0.418
PeriodIII:‘30Yr Fixed Mtg Rate‘	73.787	6.370	11.583	0

Table 23: Summary of Model 12

term	estimate	std.error	statistic	p.value
(Intercept)	-19.064	27.169	-0.702	0.483
PeriodII	77.191	65.090	1.186	0.236
PeriodIII	-193.336	41.119	-4.702	0.00000
‘30Yr Fixed Mtg Rate‘	-0.477	6.798	-0.070	0.944
price_per_square	-0.013	0.003	-3.893	0.0001
median_square_feet	0.005	0.001	4.889	0.00000
total_listing_count	-0.016	0.017	-0.913	0.361
PeriodII:‘30Yr Fixed Mtg Rate‘	-16.139	19.850	-0.813	0.416
PeriodIII:‘30Yr Fixed Mtg Rate‘	71.304	12.667	5.629	0.00000

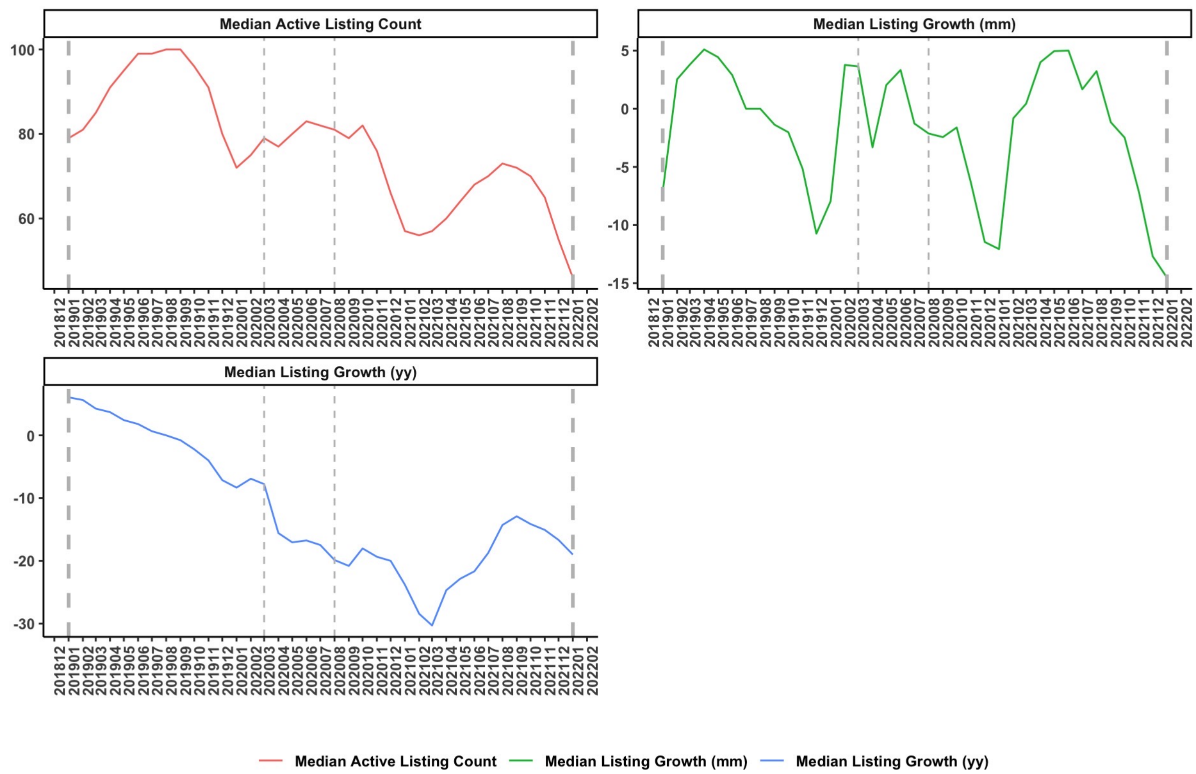

Figure 9: Housing Supply from January 2019 to January 2022

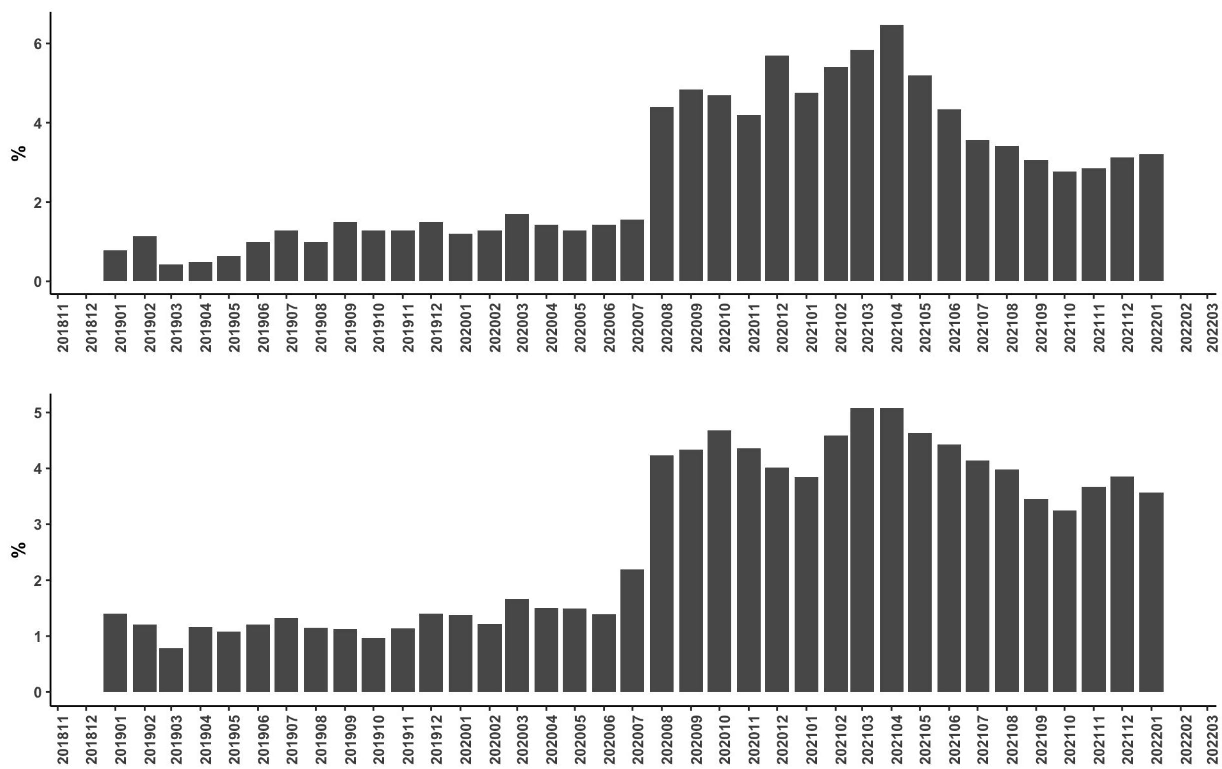

Figure 10: Distribution of Outliers across Months: Demand Score Yearly Growth
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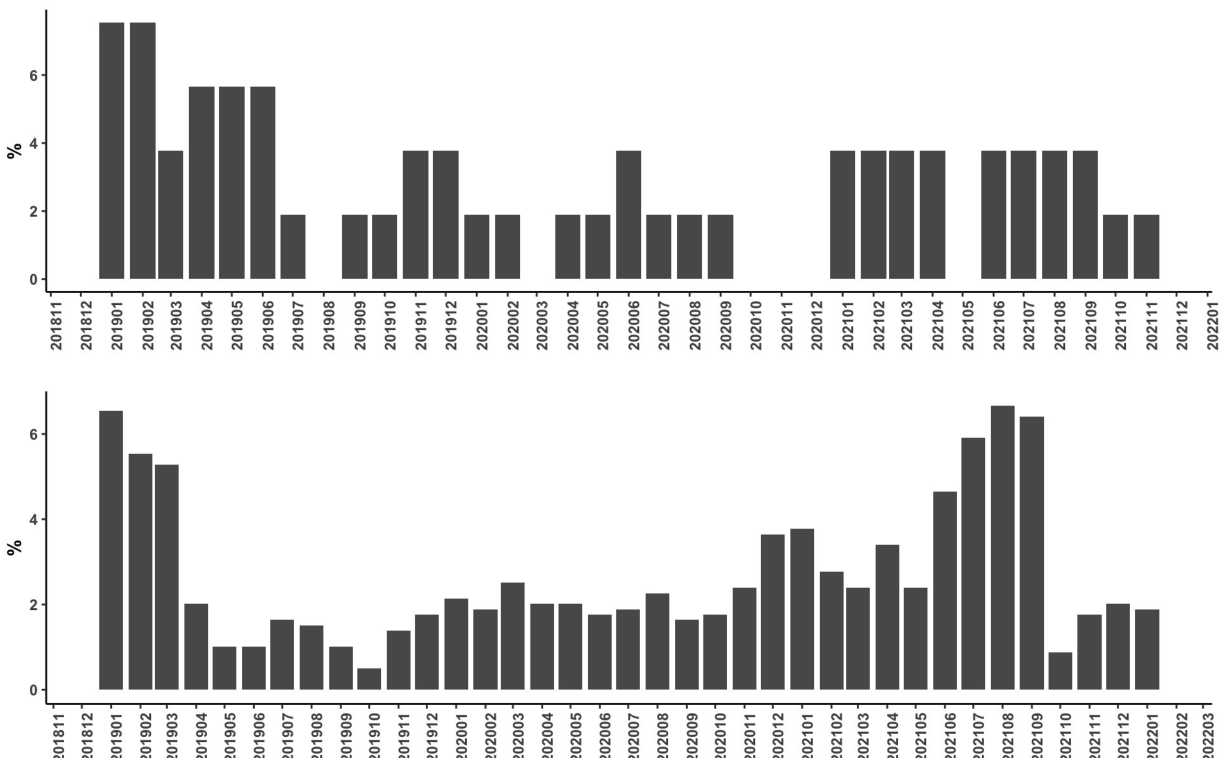

Figure 11: Distribution of Outliers across Months: Total Listing Yearly Growth [16]

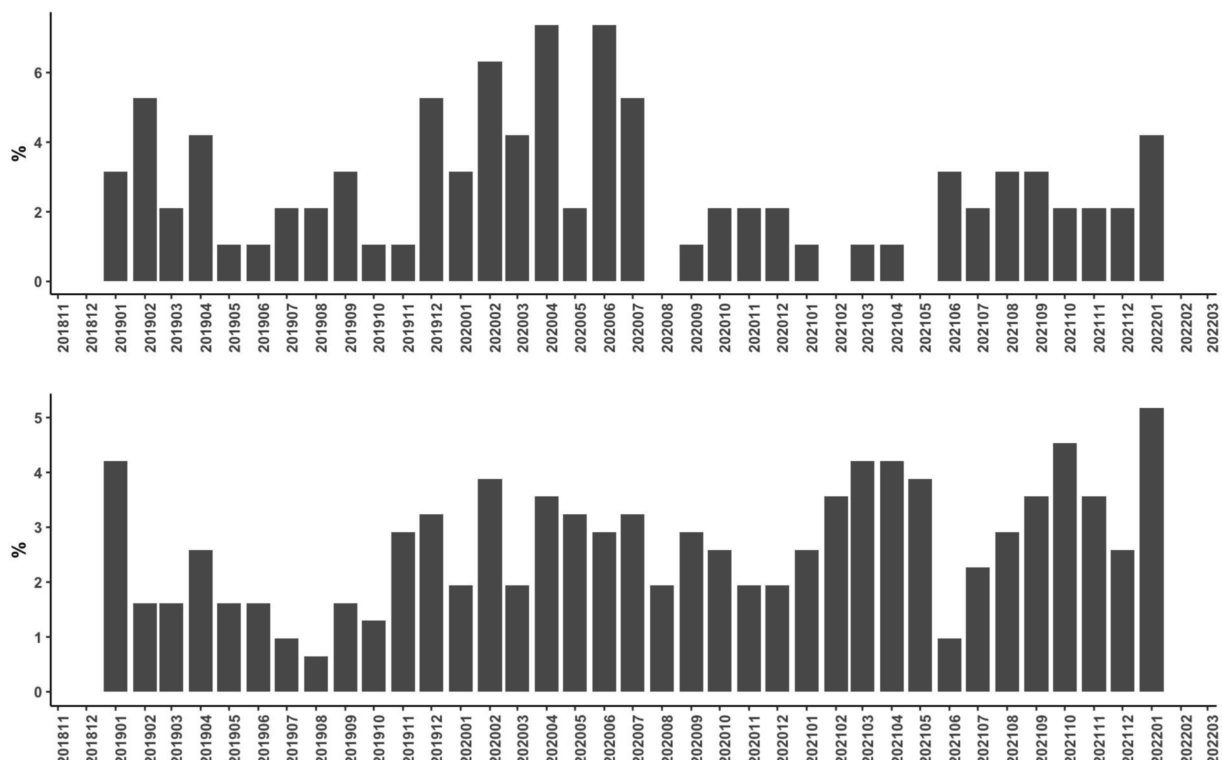

Figure 12: Distribution of Outliers across Months: Listing Price per Sqft Yearly Growth [17]

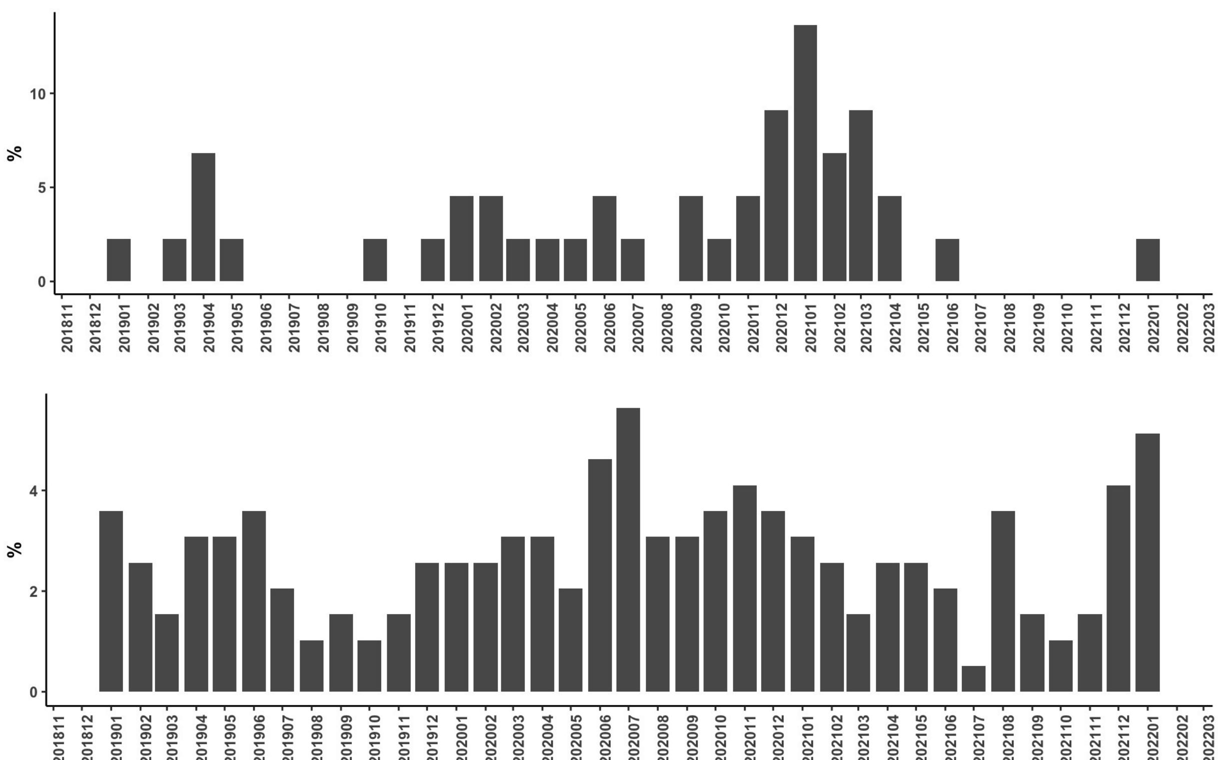

Figure 13: Distribution of Outliers across Months: Listing Size Yearly Growth
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