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Housing Supply and Liquidity in the COVID-19 Era

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Working Paper 22-02

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Abstract

We document changes in national housing supply and liquidity during the COVID-19 era using a suite of monthly indices, ranging from summary statistics (mean and median time on the market, proportion of homes sold, etc.) to more advanced econometric indices that can address censoring and unobserved heterogeneity. Our results indicate a sharp structural break in most of the indices near the start of COVID-19 in March 2020, though each index's most likely break date varies by a few months. Our findings suggest that the start of the pandemic saw a supply decrease, followed by an immediate and sustained price increase. Listings became more likely to be withdrawn, but those that sold did so faster relative to pre-COVID levels, indicating a change in the distribution of housing market liquidity. Finally, our results suggest that there were different types of structural breaks, specifically changes in the level, slope, and seasonality of the indices.

Keywords: housing supply · housing liquidity · COVID-19 · structural breaks

JEL Classification: C22 · R30 · R31

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1. Introduction

COVID-19 caused major disruptions to the health and the economy of the United States.[1] One large sector of the economy that COVID-19 has impacted is the housing market. For example, the Federal Housing Finance Agency House Price Index (FHFA HPI®) reveals unprecedented price appreciation during the COVID period, with year-over-year (seasonally adjusted) appreciation sustaining double-digit increases since October 2020. Additionally, the media has pointed out that COVID-19 has affected home construction (Mutikani, 2020), interest rates and refinancing (Goodman and Klein, 2022), and migration (Taylor, 2020), among other things. While much attention has been paid by the press and academic literature on COVID-19's effects on home prices, less attention has been paid to COVID's effects on housing market supply[2] and liquidity.[3] As far as we are aware, there is no systematic study of the effects of COVID-19 on housing supply and liquidity.[4] We aim to fill this gap.

To fill this gap, we construct a suite of housing market supply and liquidity indicators at the national level. We use several indices in part because there is no single, agreed-upon index, but also because by considering them jointly we are able to have a more holistic view of the housing market. The indicators are housing market indices that range in sophistication from basic summary statistics to more advanced econometric measures (Carrillo and Williams,

[1]For example, as Mutikani (2021) points out, the Bureau of Economic Analysis reported a decrease of annualized GDP of 19.2% from the fourth quarter of 2019 to the second quarter of 2020. Additionally, Kennedy (2022) argues there may be longer term consequences to the U.S. economy.

[2]Note that we do not consider new construction, so our analysis of supply is restricted to the supply of pre-existing homes.

[3]D'Lima, Lopez and Pradhan (2022) find a 1.5% price decrease in densely populated areas and a 1.4% price increase in relatively sparsely populated areas in response to shutdown orders. Wang (2021) and Zhang, Leonard and Bitzan (2022) both find evidence of price increases in several different areas of the United States. Zhao (2022) finds evidence of price increases early in the pandemic. Finally, Duca, Hoesli and Montezuma (2021) and Yiu (2021), consider international housing market responses, and argue that interest rates were important in driving home prices.

[4]Our work is most closely related to Yoruk (2022), who finds decreases in home sales and the number of new listings since the start of the pandemic in March 2020.

2019). Our results suggest three stylized facts. First, we find evidence of structural breaks at the start of COVID-19 in March 2020 for all but one of our market indicators, though the most likely break for each index occurred a few months before or after March 2020, depending upon the index. Second, the advanced econometric indices, which are constructed to address unobserved heterogeneity and censoring, appear to break later than the simpler indices which do not control for these factors. Thus, our results provide evidence for the importance of addressing these two fundamental issues when measuring housing market supply and liquidity. Finally, we see evidence of different types of structural changes that vary from index to index. These structural breaks include changes in the level, changes in slope, and also changes in the seasonality of each index.

Unobserved heterogeneity across properties and changes in the composition of homes during the pandemic is a concern of ours. For example, it may be the case that homes that transacted prior to COVID have different characteristics compared to those that transacted after the start of the pandemic.[5] Additionally, COVID-19 may have changed market conditions directly of its own accord. Hence, an analysis of housing market liquidity would be incomplete without considering how the number of homes available for sale, particularly those that didn't sell, changed during the COVID-era. To remedy this, we investigate some indices that use information from all listings, including those that did not sell.

[5]For example, D'Lima, Lopez and Pradhan (2022) show different price trends in rural versus urban areas, suggesting demand and preference changes. If homes are systematically different in rural versus urban areas, which seems plausible, then changing composition will be a factor in estimating either price appreciation or liquidity.

Our indices on supply and liquidity complement the more typical indices for homes prices.[6] For example, after learning that prices have increased, knowing whether or not liquidity or supply was constrained can lead to different policy conclusions. Additionally, several papers in the literature have documented that there may exist a lead-lag relationship between price and time on the market during the Great Recession, so that changes in the latter can be used to predict changes in the former.[7] We find similar results. Specifically, we find evidence of a negative relationship between price and TOM in the COVID era, with price increases and TOM generally decreasing as the pandemic progressed.[8] We build off of several recent papers in the literature that have constructed new methods of estimating housing market liquidity, most notably Carrillo and Williams (2019).[9]

The plan of the paper is as follows. First, we provide a brief timeline of the major events during the COVID-era that are germane to our analysis. After that we introduce our data and methodology, distinguishing between the simpler "traditional" indices and the more complex "advanced" indices. We then define structural breaks in our setting and specify how we will detect them econometrically. After that we present the results graphically and perform various structural break tests for each of the indices. Finally we discuss the implications of the results and conclude.

[6] Admittedly we abstract from interest rates in our analysis, which were at all time lows in the period, presumably driving some demand, consequently affecting liquidity. Kuttner (2012) argues that "the impact of interest rates on house prices appears to be quite modest," with a VAR model predicting a 10 basis point reduction in the long term interest rate leading to a home price increase of 0.3%-0.8%, depending upon the level of the current interest rate. We leave it for future work to investigate the specific interest rate effect during the COVID era as measuring demand is not our primary focus.

[7] For example, see Carrillo, de Wit and Larson (2015) and Keys and Mulder (2020). The latter notes that during the last financial crisis "the pattern of volume and prices during the housing market boom and bust demonstrates that prices are not a sufficient statistic for market demand, and that declines in volume may well occur before falling prices." They then argue a similar pattern emerges due to a climate risk shock.

[8] See Figure 9b.

[9] For other examples, van Dijk. Dorinth W. (2019) use a stochastic time trend (as opposed to a time fixed effect) to estimate TOM indexes in thin markets. Additionally, Genesove and Han (2012) develop a matching model to explain both buyer and seller TOM.

1.1 COVID-19 Background

The swift policy responses to the economic impacts of COVID-19 began in March 2020. The first of which was a reduction in the target Federal Funds Rate on March 5, 2020, with a corresponding decrease on March 15, 2020. In addition, the U.S. Congress passed the Coronavirus Aid, Relief, and Economic Security (CARES) act on March 27, 2020, providing a number of relief benefits to American households, namely a pause on student loan payments and direct $1,200 payments to households.[10] These measures coincided with the declaration of a nationwide emergency and designation of the COVID-19 disease as a pandemic on March 11 and 13, respectively, underlining the significance of March 2020 as the de facto start of the pandemic, or at least the start of its many policy responses.[11] We focus on the start of COVID-19 as our initial shock. Table 1 presents the events in the COVID-19 timeline that are germane for our analysis from the Centers for Disease Control and Prevention (CDC).

Table 1: Key COVID-19 Moments

Date	Event
December 12, 2019	Patients in Wuhan, China experience symptoms
January 20, 2020	First confirmed case of COVID-19 in the United States
March 11, 2020	World Health Organization (WHO) declares COVID-19 a pandemic
March 13, 2020	President Trump declares a nationwide emergency
March 15, 2020	U.S. states begin to shut down to prevent the spread of COVID-19
June 1, 2021	Delta variant becomes the dominant variant in the U.S.
November 26, 2021	WHO classifies Omicron variant

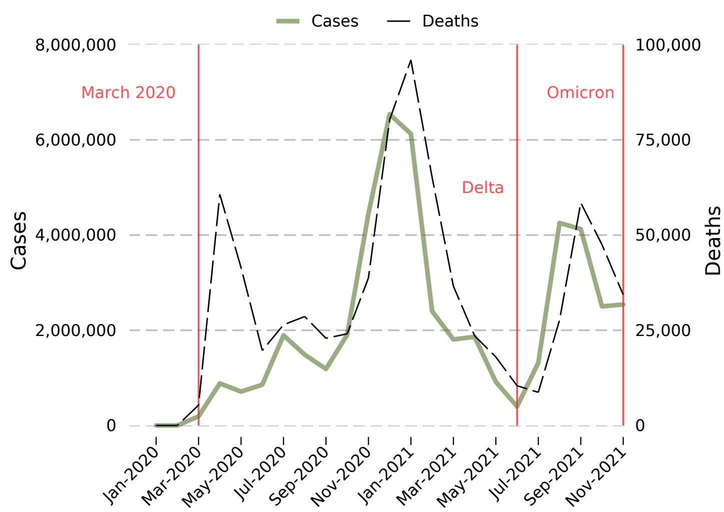
Figure 1 shows actual case numbers and deaths from COVID-19 and its variants for the United States. Apart from an initial surge in deaths at the start of the pandemic in March

[10] Early in the pandemic, Cherry et al. (2021) find that the government and private relief induced more individuals into forbearance, about 25%, which suggests "large aggregate consequences for house prices and economic activity."

[11] See the Center for Disease Control's (CDC) COVID-19 Timeline for a more detailed discussion of major events with regard to COVID-19.

2020, the number of cases typically leads the number of deaths. After the pandemic was underway, the figure indicates an increase in the number of cases and deaths in the winter of 2021 and at the start of the Delta variant. We expect the housing market responses to COVID-19 to be particularly strong during this period.

Figure 1: COVID-19 Cases and Deaths



Note: Data represent number of cases and deaths for each month reported at the national level.
Source: COVID-19 Data Repository by the Center for Systems Science and Engineering.

2. Data

Our data comes from Corelogic, which provides fairly comprehensive listings data by combining data from 156 individual multiple listing services across the United States. A multiple listing service (MLS) is a regional database of property characteristics entered by the realtor including list date, contract date, list price, beds, baths, square footage, address, etc. According to the Real Estate Standards Organization (RESO), as of October 2020, around 80% of all homes sold are in an MLS system.[12]

Our data spans January 1980 through December 2021, though some regions have data from earlier periods. In our analysis, we focus on the time period from January 2015 to December 2021. Data is sparse for counties in the west-north-central and south-west-central census divisions relative to the entire U.S., while the middle-atlantic and pacific divisions comprise a large proportion of the listings in our data. Figure 10 shows coverage across the Unites States after culling for outliers.

We remove outliers due to obvious data errors or other similarly impossible situations. Specifically, we drop observations with negative or zero list or sale prices, missing addresses or state/county FIPS codes, and missing close, contract, or off-market dates. We also drop the bottom and top percentile of list prices for each year. We restrict attention to single family residential homes, so that non-residential properties such as commercial real estate, farms, timeshares, etc., are also dropped. Additionally, we remove nested listings, defined as listings with both a list date and contract or off-market date that falls within the same dates of another listing for the same property.[13] Figure 11 illustrates the counties for which indices could be constructed for at least some time periods after removing outliers. Finally, since data was collected in December 2021, we omit indices for that month for right-censoring reasons.[14]

Some care is needed in defining a listing, particularly when a home is relisted on the market shortly after being removed from the market. Following Carrillo and Williams (2019), we

[12] See RESO (2020) for more information.

[13] For example, a home listed on June 1, 2020 and contracted on July 3, 2020 would qualify as a nested listing if that same property was also listed anytime before June 1, 2020 with a contract or off-market date after July 3, 2020.

[14] Including the last month would likely mechanically estimate slower sale times as properties listed at the start of December may have simply not been on the market long enough to have had a chance to sell.

combine two listings for a home where the first listing did not end in a sale and the home was relisted within 60 days. This helps to address any potential strategic concerns of sellers who might withdraw properties and re-list them to make the property appear to be a new listing or gain salience. The listing duration is then the sum of the individual listing durations. Note that this only applies to an unsold listing: the sale of a property always concludes a listing, regardless of when the property is listed next.

3. Housing Supply and Liquidity Indices

There is no single agreed-upon measure of either housing market supply or housing market liquidity. Different measures address different questions and have different purposes. In line with this logic, we use a suite of different indices, each of which has its own advantages and disadvantages. We group our measures of supply and liquidity into traditional measures (typically summary statistics) and more advanced measures that are derived from econometric models. Each of our indices is a monthly index at the national level. Table 2 lists all of our housing supply and liquidity indices we calculate in this paper, where the repeat proportional hazard index (RPHI) and repeat median time on the market index (RMTI) are advanced indices.

Our advanced measures (RPHI and RMTI) are two indices developed by Carrillo and Williams (2019) that employ repeat sales techniques for reasons we explain later. We expand coverage of the indices from a quarterly basis at the CBSA level for six different areas (Carrillo and Williams (2019)) to a monthly basis at the national level using 3,092 U.S. counties out of the 3,242 total U.S. counties and county equivalents.

Table 2: List of Indices

Traditional Index	Description
Count of New Listings (logged)	Sum of listings listed in a particular month.
YoY New Listings	Percent change in the count of new listings.
Percent Sold 90 days	Proportion of total listings that sold within 90 days.
Percent Sold 14 days	Proportion of total listings that sold within 14 days.
Percent Withdrawn	Proportion of total listings that did not go on to sell.
Percent of Price Drops	Proportion of total listings with sale price < list price.
Mean TOM for sold listings (logged)	Average days between list and sale date for sold homes.
Mean TOM for all listings (logged)	Average days between list and sale date or off-market date for all homes.
Median TOM for sold listings (logged)	Median days between list and sale date for sold homes.
Median TOM for all listings (logged)	Median days between list and sale date or off-market date for all homes.

Advanced Index	Description
Repeat Proportional Hazard Index (RPHI)	Estimated using methodology of Carrillo and Williams (2019)
Repeat Time on the Market Median TOM Index (RMTI)	Estimated using methodology of Carrillo and Williams (2019)

Notes: If a listing ended in a sale it is considered sold. Otherwise it is considered withdrawn. We use withdrawn and unsold interchangeably.

3.1 Traditional Descriptive Indices

The mean and median time on the market (TOM) are common statistics used to measure the speed of sale of a typical home in a given housing market.[15] These measures are often interpreted as an indication of the level of housing market liquidity in a given time period. Generally speaking, lower values of TOM mean hotter markets (i.e., relatively more buyers than sellers) as sellers can sell their properties relatively easily in a short amount of time. Some care is needed with terminology, as TOM is typically defined only for sold listings and the dates used may not be consistent across sources.[16] After grouping listings according to the process described previously, we define TOM for both sold and unsold listings. For sold listings, we define TOM of a listing as the number of days between the list date and the date the contract was signed. For unsold listings, we define the TOM as the number of days between the list date and the date the home was removed off of the market. By comparing the mean (or median) TOM for sold and all (sold and unsold) listings we can analyze the

[15]For example, both Redfin and Realtor.com use median days on the market in their regular reports of housing markets.

[16]As Benefield and Hardin (2013) point out, even when considering only sold listings, there are different definitions of time on the market in the literature. For example, some papers use contract date as the termination date while others use closing date.

consequences of censoring on these measures. Also, differences between mean and median give insights about the tails of the distribution of TOM.

To complement the typical measures of TOM we look at the fraction of homes sold with respect to three different time periods: within 14 days, within 90 days, and with any number of days. The last measure is simply the percentage of homes that sell within a given list month. We find it more convenient to work with its opposite, i.e. the percentage of homes that were withdrawn from the market before selling. Analyzing the differences between the three indices can give us additional information about how the distribution of TOM is changing.[17] For example, if the proportion of listings selling within 14 days increases but the proportion of listings selling within 90 days and any number of days decreases, then the shape of the TOM distribution is changing, whereby mass is moved to the left of the distribution and the overall measure of sold homes is reduced. In other words, some homes experienced greater likelihoods of faster sales while the overall likelihood of a sale decreased.

A more direct measure of supply uses the number of new listings on the market.[18] For each list month, we calculate the count of new listings and its year-over-year percentage change. All else equal, the more new listings there are the larger the supply of homes on the market. This will be our most direct measure of housing market supply.

Our final traditional descriptive index is the percentage of homes listed each month that experience a price drop. This measure is defined only for sold listings. For our purposes, we say a (sold) listing has experienced a price drop if the sale price is lower than the original list price. Notably this measure suffers from censoring in so far as price drops for unsold

[17] For an example of work on the distribution of TOM, see Carrillo and Pope (2012), who extend the decomposition methods of DiNardo, Fortin and Lemieux (1996) to analyze changes in the entire distribution of TOM in terms of changes in home characteristics versus changes in fundamental market conditions.

[18] Note that this excludes newly constructed homes that do not sell with a listing, as well as excludes home sales that are for sale by owner. We cannot comment on these selection effects as we lack the sufficient data.

homes have different effects than price drops for listings that go on to sell. Nevertheless, the proportion of price drops gives insights into seller behavior. All else equal, the more price drops there are, the more likely buyers are to have bargaining power. Conversely, a drop in the number of price drops indicates a market with relatively limited supply.

We also use information about price trends to compare with those of supply and liquidity trends. Specifically, we use the Federal Housing Finance Agency's (FHFA) House Price Index (HPI)® and its year over year (YoY) appreciation. We use non-seasonally adjusted (NSA) values because our other series have not been seasonally corrected.

While intuitive, the traditional measures tend to suffer from the well known statistical problems of censoring and unobserved heterogeneity (across listings). In our context, the censoring problem manifests itself as homes being pulled off of the market before they have had a chance to sell. Thus the observed times on the market for *sold* homes are likely to be less than those for the entire population, leading to estimates of time on the market that are too small if only sold listings are used. Also, if sold listings are different from the population of listings in a systematic way, say possessing on average different housing characteristics, then traditional measures may be biased.[19]

The problem of unobserved heterogeneity for the traditional measures means not taking into account differences in the composition of homes that transact over time. If sold homes are not representative of the larger population, it is important to take into account these differences when measuring housing market performance.[20] For measures of house price

[19] In a related vein for house price measurement, Gatzlaff and Haurin (1997), Gatzlaff and Haurin (1998), and Malone and Redfearn (2020) show that measures of house price appreciation from sold homes are likely to be biased using repeat sales, hedonic, and aggregation methodologies, respectively.

[20] For recent work in addressing changing composition with respect to home prices and home appreciation, see Contat and Larson (2022), who demonstrate the importance of changing geographic composition in index construction.

appreciation, the hedonic and repeat sales approaches each offer a solution to this problem by attempting to control for the observable characteristics of the home and by differencing out any time-invariant characteristics between consecutive sales, respectively. Unobserved heterogeneity tends to plague hedonic methods (by definition) and also repeat sales methods (at least to the extent that unobserved heterogeneity changes over time).

Fortunately, Carrillo and Williams (2019) develop two advanced measures of housing market liquidity that each handle both censoring and unobserved heterogeneity. Both measures exploit repeated sales of the same listing to difference out time-invariant unobserved features of a home that may influence its time on the market. These methods are data intensive in that they require a home to be sold at least twice in order to be used for estimation. Fortunately our data stretches far enough back in time to have a large number of usable observations.

3.2 Advanced Econometric Indices

We now briefly introduce the methodology behind the two advanced measures, and refer the reader to Carrillo and Williams (2019) for further details. We adopt their notation for expositional ease. The first advanced measure that we use is a proportional hazard model called the Repeat Proportional Hazard Index (RPHI).[21] The core assumption of this approach is that hazard rates are multiplicatively separable into a common term (usually called the baseline hazard) that varies over time but is the same for all homes, and into an idiosyncratic term that varies by home but not over time.[22] Carrillo and Williams (2019) then marry this idea with a repeat sales methodology to "difference out" the idiosyncracies

[21] See Cox (1972) for the seminal reference and Wooldridge (2002) for a more recent textbook treatment on proportional hazard models.

[22] In other words, the proportional hazard assumption maintains that if property A is twice as likely to sell as property B in the current time period, then A will always be twice as likely to sell as B in all future time periods, provided of course that both properties haven't yet sold at that time.

for each home.

More formally, the hazard rate $\lambda_{it}(y)$ for home i at calendar date t that has already been on the market for y days is:

$$\lambda_{it}(y) = \exp(\beta_t) \times \exp(\alpha_i) \times \lambda_0(y) \tag{1}$$

The $\lambda_0(y)$ term accounts for changes in the hazard rate due to how long the property has already been on the market, and is common for all homes. The $exp(\alpha_i)$ term accounts for unobserved heterogeneity of home i, i.e. the property-specific characteristics that do not change over time.[23] Finally, the $exp(\beta_t)$ term accounts for changes in the hazard rate due to changing market conditions faced by all homes, akin to time fixed effects in a linear regression.

By differencing across consecutive listings, integrating, taking logs, and conditioning on a subset of the sample, one can estimate the original hazard formulation using the following logistic specification, where the coefficients β on the right hand side below are the same as those given in (1):

$$Pr(V_i^2 \geq V_i^1 | W_i = 1) = \frac{\exp(\beta_{t_i^1})}{\exp(\beta_{t_i^2}) + \exp(\beta_{t_i^1})} \tag{2}$$

Here $V_i^s = \min\{Y_i^s, C_i^s\}$ is the minimum of the time on the market Y_i^s (observed only for sold homes) and the censoring time C_i^s (observed if home did not sell and was pulled off market) for property i for its s^{th}-listing. Note that V_i^s is always observed.[24] The superscripts $s = 1, 2$

[23] Accounting for unobserved heterogeneity that changes over time is well beyond the scope of this paper.
[24] If the listing sold, then $V_i^2 = Y_i^2$ while if the listing did not sell $V_i^s = C_i^s$.

indicate the sequential number of the listing, so that for example $\beta_{t_i^2}$ represents the coefficient for the time at which home i was listed for the second time in a pair of repeat listings. The conditioning variable W_i is equal to 1 if either (a) both the first and second listings sold, or (b) if one of the listings sold and its time on the market is shorter than the censored time for the other (unsold) listing. In this way we can estimate the RPHI $\mu_t = exp(\beta_t)$ for time t using a logistic regression on a particular sub-sample of data, where the explanatory variables indicate the times of sales.

The second advanced measure is the Repeat Median TOM Index (RMTI). The strategy with this index is that if the median time on the market is stationary (conditional on any differences due to listing period), then one can start with:

$$\log(Y_{it}) = \beta_t + \alpha_i + \varepsilon_{it} \tag{3}$$

and then take medians and differences to get:

$$Med(\log(Y_i^2) \mid X_i) - Med(\log(Y_i^1) \mid X_i) = \beta' X_i \tag{4}$$

As before, the unobserved heterogeneity α_i term has been successfully differenced out, a step that requires repeated sales of the same home. The idea is that roughly the difference step takes care of the unobserved heterogeneity while the median step takes care of the censoring. The right hand side β coefficients of (4) are the same as those of (3), allowing us to estimate the RMTI.

Unlike the RPHI, higher values of the RMTI imply that a home is likely to spend a longer time on the market, all else equal. As such, we follow Carrillo and Williams (2019) and use the inverse of the RMTI for easy comparison with the RPHI. In this way both the RPHI and inverse RMTI are positive measures of home liquidity, so that higher values of these indices mean that homes are likely to sell faster.

3.3 Structural Breaks

To complement visual inspection of the graphs and to provide more rigorous analysis, for each index we test for structural breaks in two different models. Each model allows for different types of structural change that could've taken place due to the COVID-19 pandemic. One addresses possible non-stationarity using a deterministic time trend while the other uses a stochastic time trend in the form of an auto-regressive (AR) process. Specifically, the first model uses a linear time trend and seasonal effects to test for breaks in the intercept, slope, and seasonality in each index. To use more standard methodology, we introduce our second model, which we take to be our preferred model. The second model uses an auto-regressive process of order two (i.e., AR(2) process) with seasonal effects to test whether COVID-19 had transient effects or were permanent, as well as tests for breaks in seasonality.

Before estimating an index, we first conduct a Dickey-Fuller test to detect the presence of a unit root. Results for these tests are located in the last column of Table 3. If the tests suggest the series has a unit root, we difference the series and adjust our specification accordingly before performing estimation. Additionally, for count variables, mean TOM, and median TOM, we convert the index into log terms to deal with possible heteroskedasticity.

3.3.1 Linear Time Trend with Seasonal Effects

Let y_t be the index in question. A simple model relates y_t linearly to time t and includes seasonal effects m_t.[25] If y_t has a unit root, then the difference $\Delta y_t = y_t - y_{t-1}$ is used in its place. To test for a structural break at time t_0 one could use the following model:

$$z_t = \beta_0 + \beta_1 t + \beta_2 \mathbf{1}_{t>t_0} + \beta_3(\mathbf{1}_{t>t_0} \times t) + m_t + n_t \mathbf{1}_{t>t_0} + \varepsilon_t \tag{5}$$

where $z_t = y_t$ if y_t does not have a unit root and $z_t = \Delta y_t$ if y_t has a unit root. Here $\mathbf{1}_{t>t_0}$ is an indicator variable equal to one if $t > t_0$ and zero otherwise. In our setting, t_0 corresponds to the start of COVID-19, i.e. March 2020. Without a unit root, the coefficients β_2 and β_3 represent changes in the intercept and slope of the index, respectively, holding seasonal effects constant. With a unit root, β_2 and β_3 represent changes in the intercept and slope of the *difference* of the index, which one could interpret as change in the slope and rate of increase in the slope of the original level series y_t. Seasonal fixed effects are also allowed to change at the break date t_0, where m_t and $m_t + n_t$ are the seasonal fixed effects before and after t_0, respectively.[26] We interpret changes in the seasonal effects, represented by n_t, as changes in seasonality induced by COVID-19.

Running a statistical test on the joint hypothesis $H_0 : \beta_2 = \beta_3 = 0$ would then help provide evidence for whether or not a different time trend occurred after the start of COVID-19, holding fixed the seasonal effects. To test this, we perform a Likelihood Ratio (LR) test

[25] More advanced methodologies might employ multiple structural breaks, multiple covariates, and allow partial breaks (i.e., a change in the coefficients of some but not all variables). See Bai and Perron (2003) for a review of such methodology, and Knoll, Schularick and Steger (2017) for a recent application with home prices.

[26] We define spring as March - May, summer as June - August, fall as September - November, and winter as December - February.

for this hypothesis.[27] We test for changes in seasonality with a joint F-test on the vector of changes in seasonal fixed effects: $H_0 : n_t = 0$. Of course, we also test for *any* change in coefficients using $H_0 : \beta_2 = \beta_3 = n_t = 0$.

In addition to testing for a structural break at a specific time (March 2020), we also estimate the most likely time for a structural break for each series using the supremum of all the test statistics at each month. In other words, we use the time where the test statistic is the largest to determine where the break is most likely to occur. In order to minimize false positives, this approach adjusts the critical value to account for the fact that the break date is not known in advance.[28] Note that as Andrews (1993) points out, this supremum test is valid even if the underlying series is non-stationary under a null hypothesis of parameter stability.

After determining the most likely break date econometrically, which we call the suggested break date in Table 3, we then classify which breaks are present *at the suggested break date*. For the linear time trend model, we say that there was a change in the level value of the index if the intercept (i.e., constant) has changed, which in our model is a statistically significant β_2. Similarly we say that there was a change in the growth or slope of the index if β_3 is statistically significant. Finally, we say that there was a structural break in seasonality if n_t is statistically significant.

3.3.2 $AR(2)$ process with seasonal effects

[27] While it is well known that the Likelihood Ratio (LR), Wald, and Lagrange (i.e. "slope") tests are all asymptotically equivalent, in smaller samples they may lead to different conclusions (Wooldridge, 2002). Given our time series framework, this may be particularly germane, so we use the LR test.

[28] See Davies (1987) for a seminal reference, Hansen (2001) for a quick introduction, and Perron (2007) for more recent surveys on the econometrics of structural breaks.

Our second model is a more traditional time series model. Each index follows an auto-regressive process of order 2, i.e. $AR(2)$. Some care is needed in interpreting the coefficients in the model as some indices were differenced before estimation to account for unit roots. Thus for series without unit roots we use the level index y_t as the dependent variable, while for series with unit roots we difference and use the difference as the dependent variable. More formally, our second model is:

$$z_t = \beta_0 + \beta_1 z_{t-1} + \beta_2 z_{t-2} + m_t + n_t \mathbf{1}_{t>t_0} + \alpha_1 \mathbf{1}_{t=t_0} + \alpha_2 \mathbf{1}_{t>t_0} + \epsilon_t \tag{6}$$

where again $z_t = y_t$ for a series y_t without a unit root and $z_t = \Delta y_t = y_t - y_{t-1}$ for a series with a unit root.

For series without unit roots, the interpretation of coefficients is straightforward. The α_1 term captures a temporary shock in the level of the index while the α_2 term captures a persistent shock in the level of the index. A temporary shock would decay in the usual fashion as a consequence of the auto-regressive process. In contrast, a persistent and permanent shock effectively shifts the constant in the regression. If y_t is stationary, then it is easy to show that shifts in the constant are associated with shifts in the expected value $E[y_t]$, so that α_1 and α_2 capture changes to the expected value of the index. Finally, as before the n_t parameters represent changes to the seasonal fixed effects.

For series with unit roots that we have differenced, the interpretation of the coefficients is slightly changed. Now α_1 represents a one time increase in the *difference* of y_t, which is equivalent to a permanent increase in the *level* of y_t. Also, α_2 represents a permanent increase in the *difference* of y_t, which is equivalent to a permanent increase in the *slope* of y_t. Finally, n_t represents a permanent change to seasonal effects for the difference of y_t, which is equivalent to a change above the expected change in seasonal coefficients.

We test for structural breaks with $H_0 : \alpha_1 = \alpha_2 = 0$ using an F-test. Additionally, as before non-zero values of n_t provide further evidence of structural changes. We test for this using $H_0 : n_t = 0$. We indicate in Table 3 if there is evidence of either break at March 2020. Then, using the suggested break date from the linear trend model, we test for the specific types of breaks using the previously suggested F-tests at that suggested break date for each index.

4. Results and Discussion

In our data, we say that a listing is sold if it has a close price and either a close date or contract date. Otherwise we say that the listing is unsold. As mentioned previously, this classification possess problems only at the end of the sample, where a property might have been listed too closely to the data collection time for either the listing to have been removed or to have sold. To address this concern, we do not report index values for the last month in our sample. Table 3 summarizes our results for structural breaks for each of our two models. Table 4 lists all of the specific parameter estimates at the suggested break dates for each of the two models.

4.1 Traditional Index Analysis

Figure 3a illustrates the trend of new listings over time. As evident from the graph, there are strong seasonal patterns for new listings. Additionally, we see a general reduction in the amount of new listings starting March 2020. Due to strong seasonal effects and our linear time specification, it is no surprise that we don't find evidence of a structural break in Table 3. To better identify changes in trend for new listings, we now turn to year-over-year changes, where in principle seasonal effects should cancel themselves out.

Figure 3b illustrates the year-over-year percent change in new listings which shows changes in the trend for the start of the pandemic, the Delta variant, and the Omicron variant. We see a clear decrease at the start of COVID-19 in March 2020 and also for the Delta variant around April 2021. There also appears to be a drop corresponding to the Omicron variant around November 2021, though this appears too close to the end of our sample to make any definitive statements.

We did not find strong evidence of a structural break for either the count of new listings or the year over year new listings in either of our two specifications. For the latter, this is likely due to the sharp partial recovery afterwards, which we did not model. Nonetheless, the graphs suggest that the supply of homes on the market available for sale was disrupted by COVID-19. To further investigate we calculated the number of listings before and after March 2020, for 12 and 21 month windows. For the 12 month window we find, on average, a 15,000 decrease in the number of new listings while for the 21 month window we find a 22,000 decrease in new listings. Alternatively, we calculated that the peak of new listings decreased by roughly 28,000, or about 12%, from the pre-Covid average to the post-COVID average. We leave future work to use more sophisticated time series approaches to formally model the shocks and recoveries that mechanically show up in the seasonal year-over-year series.

Figures 3a and 3b also illustrate the percent of withdrawn listings. Prior to COVID-19, the percentage of withdrawn listings was relatively stable around 16%. However, graphically we see that around April 2020 there was a sharp increase in the percentage of homes that did not sell. As the reference lines indicate, there was a dramatic and sustained increase from around April 2020 to Jan 2021. During this time period the percentage increased (approximately) from 15% to over 45%, so that the proportion more than tripled. Structural Break tests indicate that the most likely break occurred several months later in July 2020. There is mixed evidence of breaks in the two models. The linear model suggests intercept, slope, and seasonal breaks while the AR(2) finds only small evidence of seasonal shocks. Though some of the increase in the percentage of withdrawn listings at the end of our sample is likely due to data collection censoring as we previously mentioned (even after discarding the last month's observations), we still see a large increase in the percentage of withdrawn listings, except in the last month. Indeed, in November 2021 there was actually a *decrease* in the percentage of withdrawn listings. This provides some evidence of an increase in the probability of a home selling at the end of our data sample because this more than compensates for the mechanical increase in withdrawn percentage due to censoring.

Figure 7 illustrates the proportion of listings sold within 14 and 90 days in the 2015-2021 time period. Note that the proportion of very fast sales, i.e. within 14 days, increased at the start of COVID and did not return to similar values seen before COVID until well into the pandemic around the end of our sample in Dec 2021. In contrast, the percent sold within 90 days experienced a brief increase (likely due to an increase in homes that sold very fast), but then experienced lower levels relative to pre-pandemic values. Coupled with the fact that the percentage of withdrawn listings (i.e., sold within any amount of days in our sample) increased in our sample indicates a change in the distribution of TOM. Indeed, as Figures 2a and 2b indicate, the pre-COVID and post-COVID periods saw a first-order stochastic shift in time on the market, where homes across the distribution are likely to sell faster in the post-COVID period. As the graphs indicate, this is true for both a 12 month and 21 month window before and after the start of the pandemic.

Figure 4 illustrates both the mean and median TOM during our sample period. Note that the mean tends to be greater than the median, for both sold and all listings, indicating that the distribution of TOM is relatively right skewed. In other words, the homes that stay on the market the longest do so for disproportionately long times. Additionally, in agreement with Carrillo and Williams (2019), we find evidence of the consequences of censoring in that sold and unsold metrics lead to different index values, where TOM for sold homes is smaller (on average) than the the TOM for all homes listed on the market. The *changes* in trends across both mean and median, as well as sold and unsold, appear very similar, so that a decrease (increase) in one index is followed by a proportional decrease (increase) in the other.

Figure 4 also indicates a downturn in mean and median TOM starting around March 2020 that has yet to recover, at least as of the last month in our sample (Nov 2022). For both sold and all listings' median TOM, graphically there is evidence of a structural break at March 2020, though our structural breaks test give different results. This is likely because we ran our results on the difference of logged mean/median TOM, rather than the raw series. Nonetheless, except for logged median TOM which has a later suggested break point, all of the evidence points to a break in TOM indices around November and December of 2019, where to be clear the date corresponds to the month in which the property was listed. In other words, the effects of COVID on shorter selling times were first felt by properties listed at the very end of 2019. For a ballpark comparison, for the period Jan 2015 - Dec 2019, the mean and median TOM for sold listings were 119 and 63 days, respectively. For properties listed in Nov 2019, this would correspond to a sale date around March and January of 2022, respectively.

Figure 6 illustrates the percentage of price drops in the 2015 - 2021 period. As with median TOM, we see evidence of a sharp decrease in this index around March 2020. Structural break tests suggest the break occurred later in June 2020. We find strong evidence of all types of structural breaks, indicating a clear break in selling behavior regarding changing price. In short, sellers were unambiguously less likely to reduce prices after the start of the pandemic.

Finally, to complement our supply and liquidity indices we also analyze two price-related indices. The first is the monthly purchase-only FHFA's House Price Index (HPI), which is at the national level. We use the nominal and seasonally unadjusted version for ease of comparison with the other indices, which are also not seasonally adjusted. Figures 8a - 9c graph changes in price levels and appreciation against other traditional indices. We see evidence of a sharp increase in price appreciation at the start of the COVID-19 pandemic in March 2020, though the structural break test indicates that the structural break likely first occurred later in June 2020. Surprisingly we find that the percentage of withdrawn listings and year-over-year HPI appear to be highly correlated, as evident from Figure 8b. Figure 6 shows that the number of homes with price drops, i.e. where the property sold for a price lower than the list price, decreased sharply at the start of COVID-19, in tandem with the increase in withdrawn listings. Graphically the trend in year over year price appears to be negatively related to both mean and median TOM. Apart from the year over year AR(2) model which finds limited evidence of a seasonal structural break, our results suggest there may have been a break in trend and also in seasonal effects in home prices, both in levels and appreciation.

In summary, the traditional indices paint a relatively straightforward picture. At the start of the pandemic, new listings decreased and price appreciation started to climb quite quickly. Both mean and median time on the market started falling, as homes were being sold in shorter times. However, this needs to be qualified with the fact that the proportion of listings that did not sell increased from around 15% to around 60% at its peak. While seemingly counter-intuitive, we believe this could be the result of a shortage of supply. Home sellers often are home buyers as well. A home owner may choose to delay a transaction until he or she has secured a future home in which to live. This could be reflected in the data as a seller whose listing is on the market but does not exit the market. The fact that the proportion of listings sold within a very quick time frame (14 days) saw a large increase before resuming to previous levels could be due either to waiting on a home purchase or sellers seeing rapid price appreciation and deciding to hold out for very high prices. We leave it to future research to determine the exact mechanism.

4.2 Advanced Index Analysis

Figure 5 illustrates the differences between the inverse RMTI and the Median TOM. One would expect them to be inverses to some extent, on the one hand, since the RMTI is at its core a measure of the median TOM. However we see the indices are not perfectly inversely related, suggesting that the RMTI's correction for censoring and unobserved heterogeneity is not without warrant. We see from Figure 5 that the break in the (inverse) RMTI did not occur until much later, around Dec 2020, where there was a sharp increase. Moreover, the sharp increase was sustained for a few months before the RMTI flattened, only to experience another sharp increase shortly after the introduction of the Delta variant in June 2021.

Figure 5 also shows the RPHI and RMTI during our sample period. Both experience similarly sized shocks at similar times. Both are relatively flat until Dec 2020, where there then is a sharp sustained increased. This increase is followed by another relatively flat period until July 2021 for the RMTI and August 2021 for the RPHI, where the index starts increasing again. We take this to indicate that while the RPHI and RMTI have different methodologies, they may be close substitutes in practice. The one difference is that Figure 5 suggests that the RPHI is flatter over time, while the RMTI seems to vary more over time. Structural break tests suggest a later break date of Sept 2020 for the inverse RMTI and an earlier break date of Dec 2019 for the RPHI. We believe that these differing results point out a need to incorporate more advanced time series analysis that can handle multiple structural breaks. We touch more upon this in the conclusion. Nonetheless, we do find strong evidence of all types of our structural breaks for the advanced indices.

4.3 Discussion

The breaks in our indices paint a clear picture of the housing market in the COVID-era. At the start of the pandemic (March 2020) there was a decrease in new listings, thus decreasing the supply on the market. Eventually in the summer of 2020 listings started to increase, though not to their pre-COVID levels. This decrease in supply coincided with a sharp increase in price appreciation. Thus we see evidence that the surge in prices due to COVID-19 was at least partially driven by a lack of supply; for example see Figure 9b, which shows a clear negative relationship between price and median TOM over time.

For the few homes that were listed on the market, there were dramatic changes in their performance. Shortly after the pandemic we see a dramatic increase of the percent of homes that were withdrawn from the market, suggesting a reduction in the probability of sale. If a home did sell however, its expected (and median) time on the market also saw a reduction. One possible explanation is that due to the lack of supply, sellers were either holding out for higher prices or could not find a replacement property to which to move. Apart from the general uncertainty of the period, rapidly appreciating home prices and low interest rates during this period may have provided incentives for home owners to stay put. Home owners saw the values of their assets significantly grow and also may have been reluctant to give up a low interest rate on a recently refinanced mortgage despite the cost of financing a home purchase being relatively low.

The more advanced measures tend to break later, though we cannot identify a precise break date due to the likely presence of multiple break dates. Graphically, we see that after the initial jump, the advanced indices remained relatively flat until summer of 2022. Compared to pre-COVID levels, this jump corresponded to approximately double their previous trends. Both indices had a slight negative time trend prior to COVID-19, but now have positively-sloped time trends. Qualitatively, the flattening of the indices in the summer of 2022 is not seen in the traditional measures. This, coupled with the delayed onset of changes to the RPHI and RMTI, suggest that censoring and unobserved heterogeneity are important to consider when measuring supply and liquidity of housing markets.

Using our traditional indices, we can provide some evidence that unobserved heterogeneity was the main driver of differences. For example, between March 2020 and December 2020 median TOM for sold and unsold both experienced decreases though median TOM for sold properties was intuitively slightly smaller than that when including unsold homes. However this effect of censoring is relatively small. Hence one possible explanation for the divergence of traditional and advanced index levels is that between March 2020 and December 2020 there was a lot of unobserved heterogeneity that traditional indices ascribed to liquidity changes.

5. Conclusion

Housing supply and liquidity were greatly impacted by COVID-19, with the largest disruptions occurring at the start of the pandemic in March 2020. There were considerable differences between indices that controlled for censoring and unobserved heterogeneity, suggesting that traditional indices which do not account for these issues may confound changes in supply and liquidity with changes in sample composition and changes in the probability of sale. Importantly, the RPHI, RMTI, and percent withdrawn measures track changes in price appreciation very well.

In this paper we have documented and described the changes in supply and housing market liquidity in the COVID era. One issue worth exploring would be to examine any heterogeneity with respect to the increase in the proportion of withdrawn listings. For example, is there evidence of an increase in withdrawn listings across different geographies, or across different price tiers within a given geography. We leave it for future work to examine these effects and pin down a causal mechanism.

Future work could also focus on the determinants of these changes. One possibility would be to incorporate the possibility of multiple structural breaks to test for whether the different variants of COVID (Delta, Omicron) had effects on the market. Another avenue might be analyzing sample selection using hedonic characteristics, specifically looking at how the probability of sale and TOM vary across different types of homes. Additionally, more careful analysis of the distribution of TOM, for example decomposition techniques similar to that of Carrillo and Pope (2012), seems helpful for understanding what is driving the changes in liquidity. Finally, determining how changes in supply and liquidity vary across locations, say distance to CBD, seems particularly useful if buyers are finding suburban homes relatively more desirable than urban homes.

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Table 3: Single Structural Breaks for Time Series

	Linear Model			AR(2)		
Traditional Index	Break at March 2020?	Suggested Break	Type of Break(s)♠	Break at March 2020?	Type of Break(s)♠	Unit Root?
Count of New Listings (logged)‡	✓	Sept 2020	L,M	✗	-	✗
YoY New Listings◇	✗	May 2020*	-	✓	-	✓
Percent Sold 90 days	✓	April 2020	L,M	✗	-	✗
Percent Sold 14 days	✓	May 2020	L,M,S	✓	M	✓
Percent Withdrawn	✓	July 2020	L,M,S	✗	S	✓
Percent of Price Drops	✓	June 2020	L,M,S	✓	L,M,S	✓
Mean TOM for sold listings (logged)	✓	Dec 2019	L,M,S	✗	-	✓
Mean TOM for all listings (logged)	✓	Nov 2019	L,M,S	✓	M	✓
Median TOM for sold listings (logged)	✓	May 2020	L,M,S	✓	S	✓
Median TOM for all listings (logged)	✓	Nov 2019	L,M,S	✓	M	✓
Advanced Index						
Repeat Proportional Hazard	✓	Dec 2019	L,M,S	✓	L,M,S	✓
Inverse Repeat Median TOM	✓	Sept 2020	L,M,S	✓	M,S	✓
House Prices						
FHFA Purchase HPI (NSA)	✓	June 2020	L,M,S	✓	M,S	✓
YoY FHFA Purchase HPI (NSA)	✓	Sept 2020	L,M,S	✗	S	✓

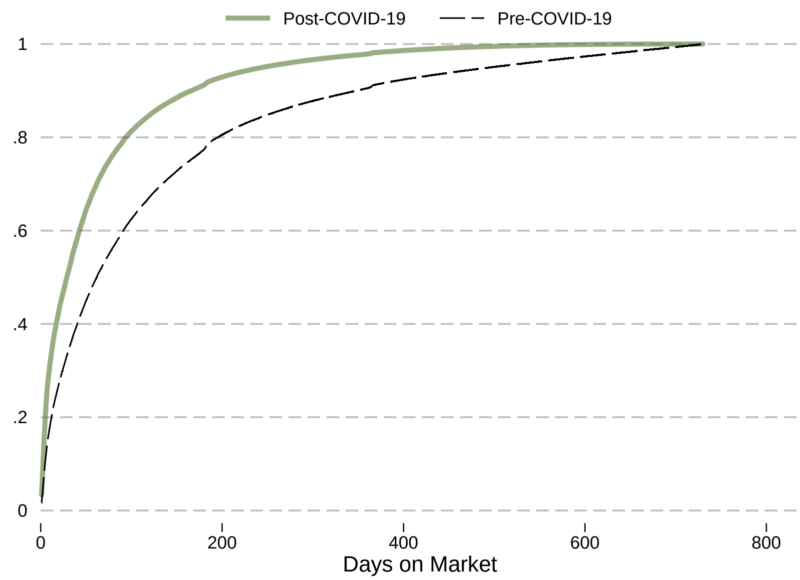
Notes: Types of Break always refer to the series estimated, and not necessarily of the base level series. Logs of series were used where indicated in parentheses. L= shift in intercept, M= shift in slope, and S = shift in seasonal effects.* means suggested break is not statistically significant.◇The difference in logs was used instead of the usual percent change formula. ‡Depending upon the specific F-test, the series breaks at March 2020 with marginal statistical significance slightly below or above the 95% level.♠The types of breaks were determined using the estimation at the suggested break date listed in this table.

Table 4: Model Estimates

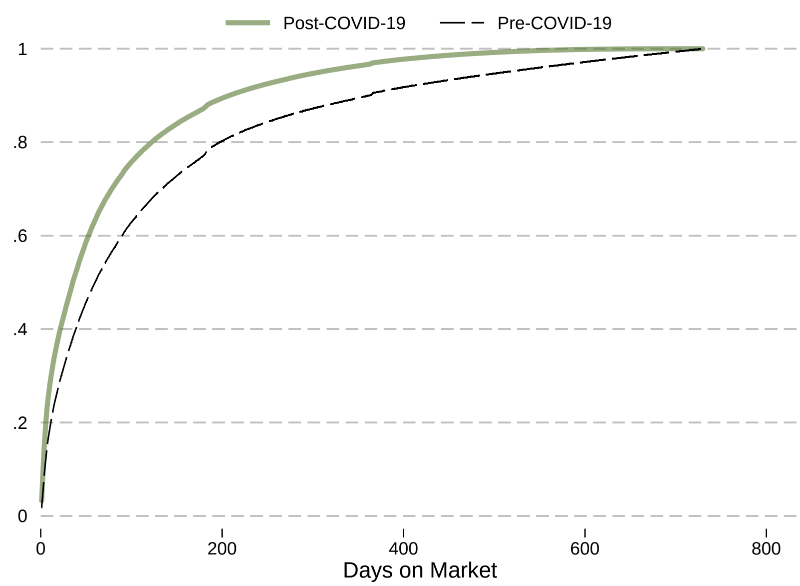
	Linear Time Trend Model				AR(2) Model	
Traditional Index	Intercept	Slope	Intercept∗ Break	Slope∗ Break	Transitory	Permanent Shock
Count of New Listings (logged)	12.39***	-0.00	22.35**	-0.03**	0.10	0.02
	(0.60)	(0.00)	(8.15)	(0.01)	(0.13)	(0.09)
YoY New Listings	0.30	-0.00	7.94	-0.01	0.44	-0.02
	(0.79)	(0.00)	(5.90)	(0.01)	(0.31)	(0.06)
Percent Sold 90 days	0.08	0.00***	13.60***	-0.02***	0.04*	0.05
	(0.12)	(0.00)	(0.79)	(0.00)	(0.02)	(0.04)
Percent Sold 14 days	-0.17	0.00**	5.47***	-0.01***	0.04	-0.03**
	(0.12)	(0.00)	(0.91)	(0.00)	(0.11)	(0.01)
Percent Withdrawn	0.34***	-0.00*	-20.30***	0.03***	-0.01	0.02
	(0.07)	(0.00)	(0.64)	(0.00)	(0.01)	(0.01)
Percent of Price Drops	1.20***	-0.00***	11.24***	-0.02***	-0.04***	-0.03***
	(0.07)	(0.00)	(0.55)	(0.00)	(0.01)	(0.00)
Mean TOM for sold listings (logged)	5.23***	-0.00	47.28***	-0.7***	-0.01	-0.11
	(0.49)	(0.00)	(2.46)	(0.00)	(0.12)	(0.09)
Mean TOM for all listings (logged)	5.11***	-0.00	46.13***	-0.06***	0.02	-0.04*
	(0.33)	(0.00)	(1.54)	(0.00)	(0.37)	(0.02)
Median TOM for sold listings (logged)	5.85***	-0.00**	30.53***	-0.04***	-0.27	0.09
	(0.65)	(0.00)	(4.94)	(0.01)	(0.56)	(0.05)
Median TOM for all listings (logged)	5.11***	-0.00	46.13***	-0.06***	0.02	-0.04*
	(0.33)	(0.00)	(1.54)	(0.00)	(0.37)	(0.02)
Advanced Index						
Repeat Proportional Hazard	3.31***	-0.00**	-70.83***	0.10***	-0.26***	0.22***
	(0.64)	(0.00)	(3.20)	(0.00)	(0.06)	(0.03)
Inverse Repeat Median TOM	5.75***	-0.01***	-119.92***	0.17***	-0.09	0.23***
	(0.45)	(0.00)	(6.10)	(0.01)	(0.09)	(0.04)
House Prices						
FHFA Purchase HPI (NSA)	-580.57***	1.19***	-2,473.2***	3.41***	2.03	2.22***
	(6.21)	(0.01)	(52.08)	(0.07)	(3.02)	(0.33)
YoY FHFA Purchase HPI (NSA)	-3.33	0.01**	-410.17***	0.57***	0.33	0.23
	(3.28)	(0.00)	(44.24)	(0.06)	(0.71)	(1.02)

Notes: Estimations performed at estimated break dates listed in Table 3. Standard errors given in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Figure 2: Cumulative Distribution of Time-on-Market Pre and Post the Start of COVID-19



(a) 21 Month Window

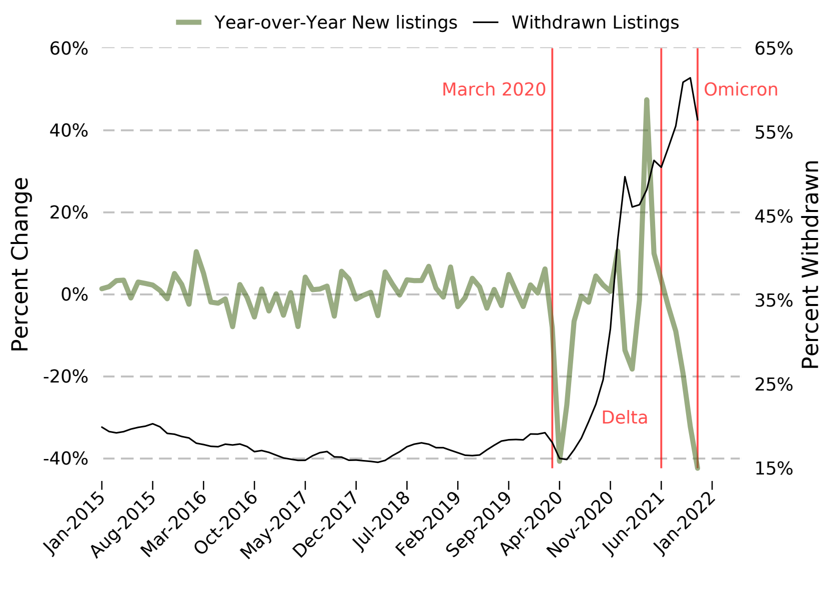


(b) 12 Month Window

Notes: Data are estimated at the national level. Pre- and Post-COVID denotes the designated number of months before or after March 2020. For 21 month periods, Pre-COVID consists of June 2018 through February 2020 and Post-COVID consists of March 2020 through November 2021. For 12 month periods, Pre-COVID consists of April 2019 through April 2020 and Post-COVID consists of March 2020 through March 2021.
Source: Multiple Listings Service data provided by CoreLogic.

Figure 3: New Listings and Withdrawn Listings, 2015 - 2021

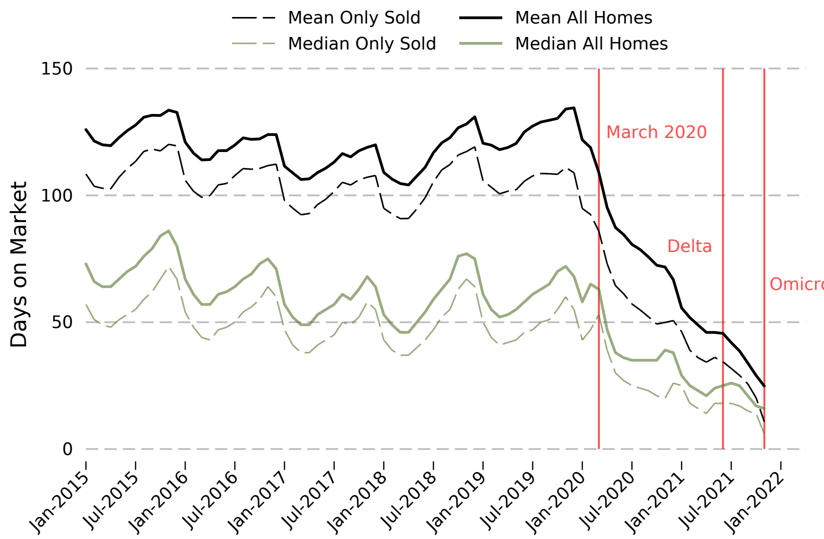
(a) Count of New Listings



(b) Change in New Listings

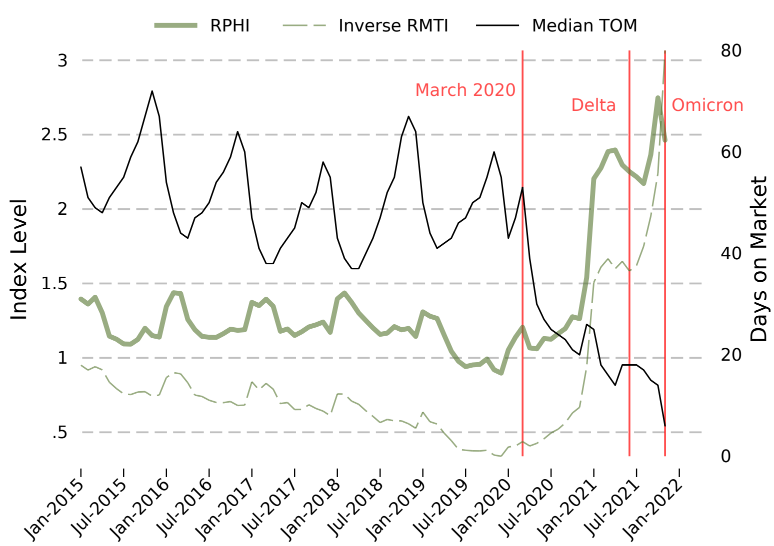
Note: Data are estimated at the national level.
Source: Multiple Listings Service data provided by CoreLogic.

Figure 4: Time-on-Market, 2015 - 2021



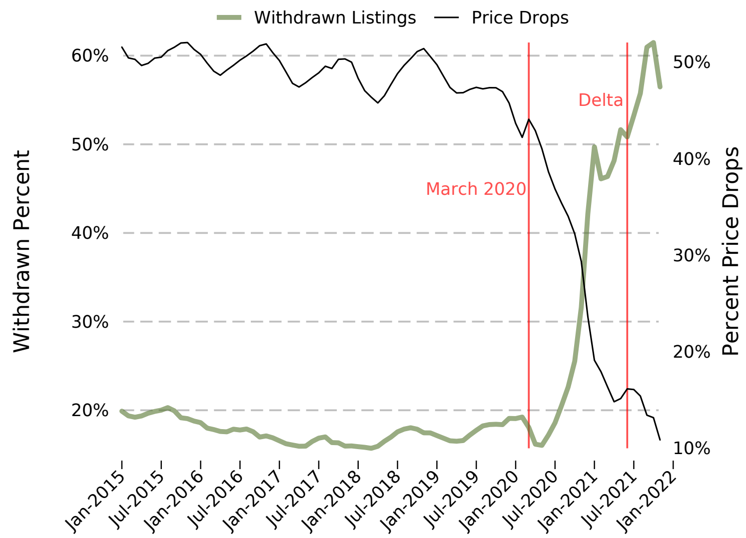
Note: Data are estimated at the national level.
Source: Multiple Listings Service data provided by CoreLogic.

Figure 5: Advanced Measures of Time-on-Market, 2015 - 2021



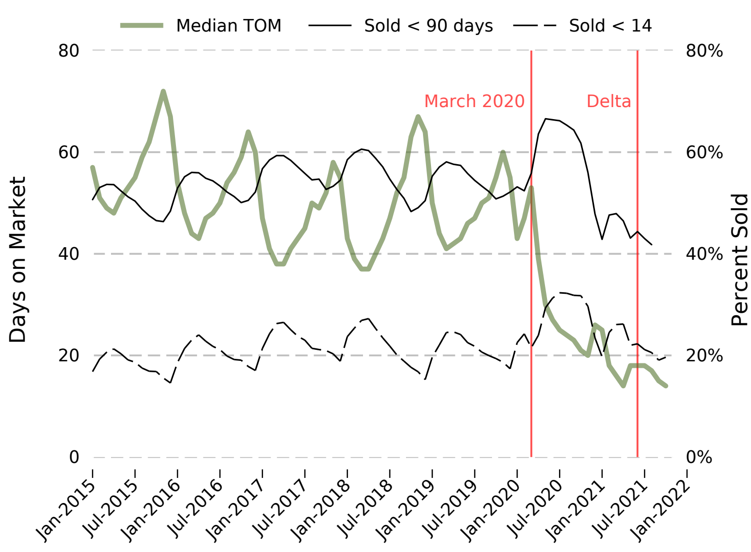
Notes: The inverse RMTI is used here to more closely compare with results of the RPHI. Both are measured a the national level. Here, median time-on-market is estimated for only sold homes.
Source: Multiple Listings Service data provided by CoreLogic.

Figure 6: Withdrawn Listings and Price Drops, 2015 - 2021



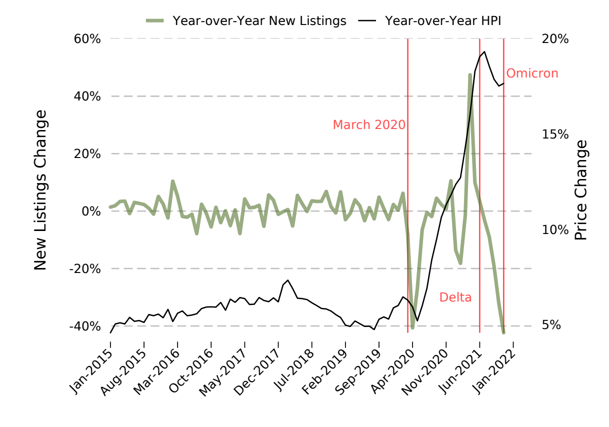
Note: Data are estimated at the national level.
Source: Multiple Listings Service data provided by CoreLogic.

Figure 7: Median TOM and Speed of Sale, 2015 - 2021

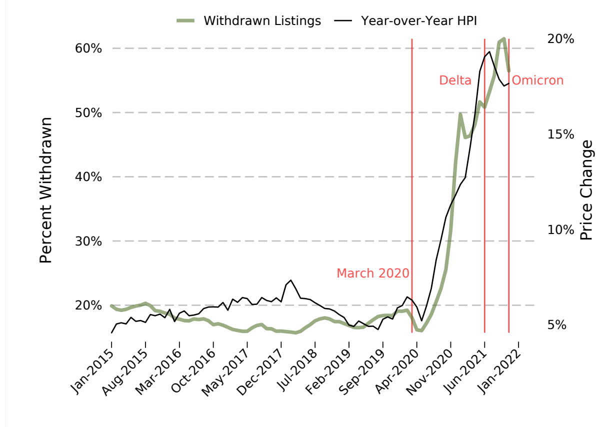


Note: Data are estimated at the national level.
Source: Multiple Listings Service data provided by CoreLogic.

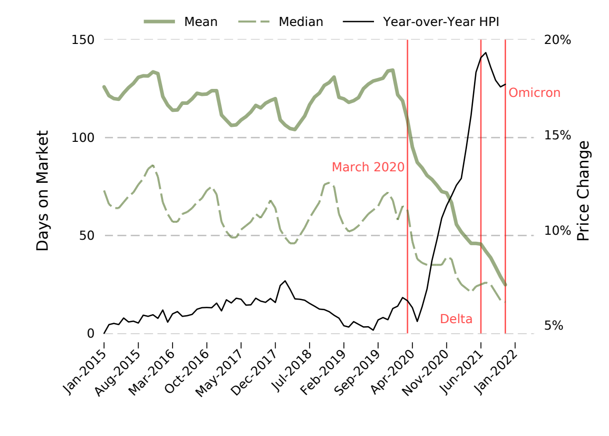
Figure 8: Supply, Liquidity, and House Prices, 2015 - 2021



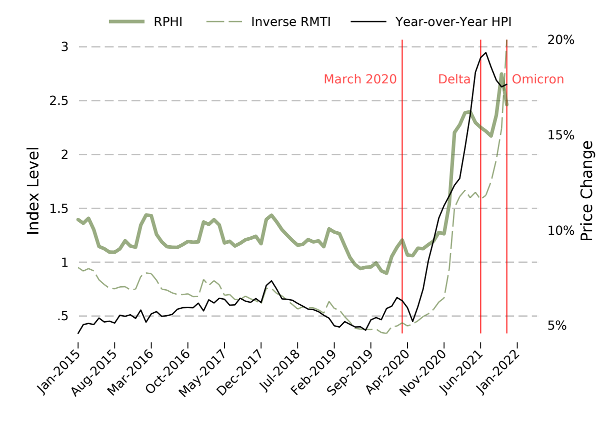
(a) Change in New Listings



(b) Withdrawn Listings



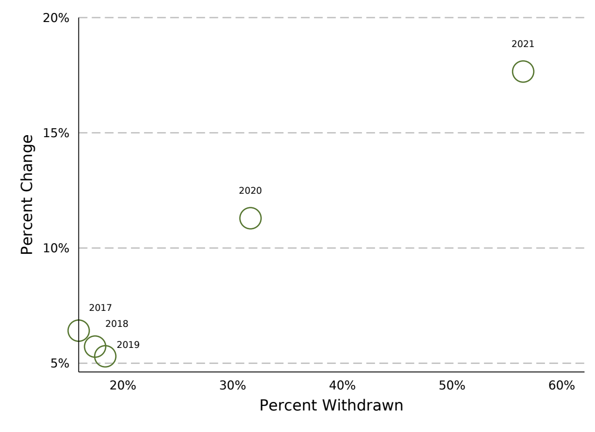
(c) Median Time-on-Market



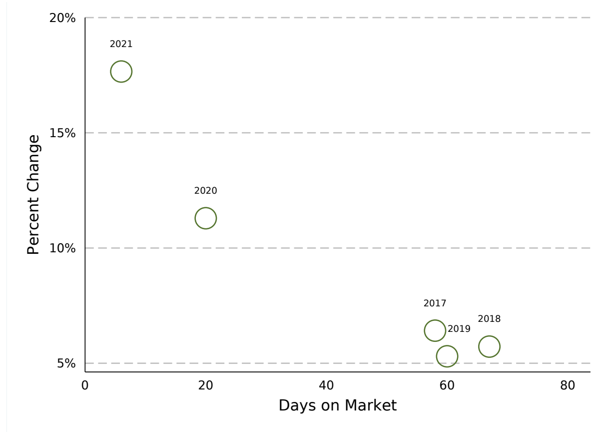
(d) Advanced Indices

Note: Data are estimated at the national level.
Source: Multiple Listings Service data provided by CoreLogic and FHFA HPI® (purchase-only, not seasonally adjusted).

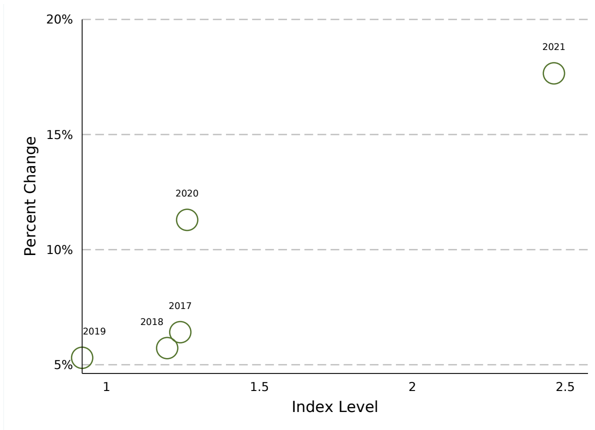
Figure 9: Supply, Liquidity, and House Prices



(a) Withdrawn Listings



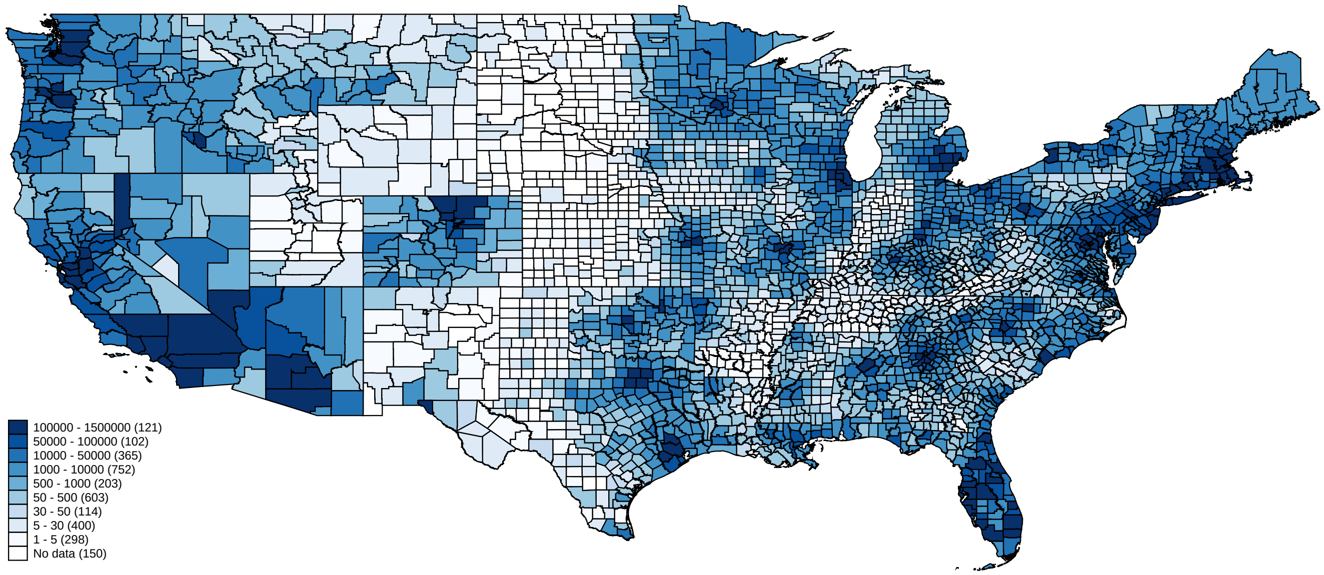
(b) Median Time-on-Market



(c) RPHI

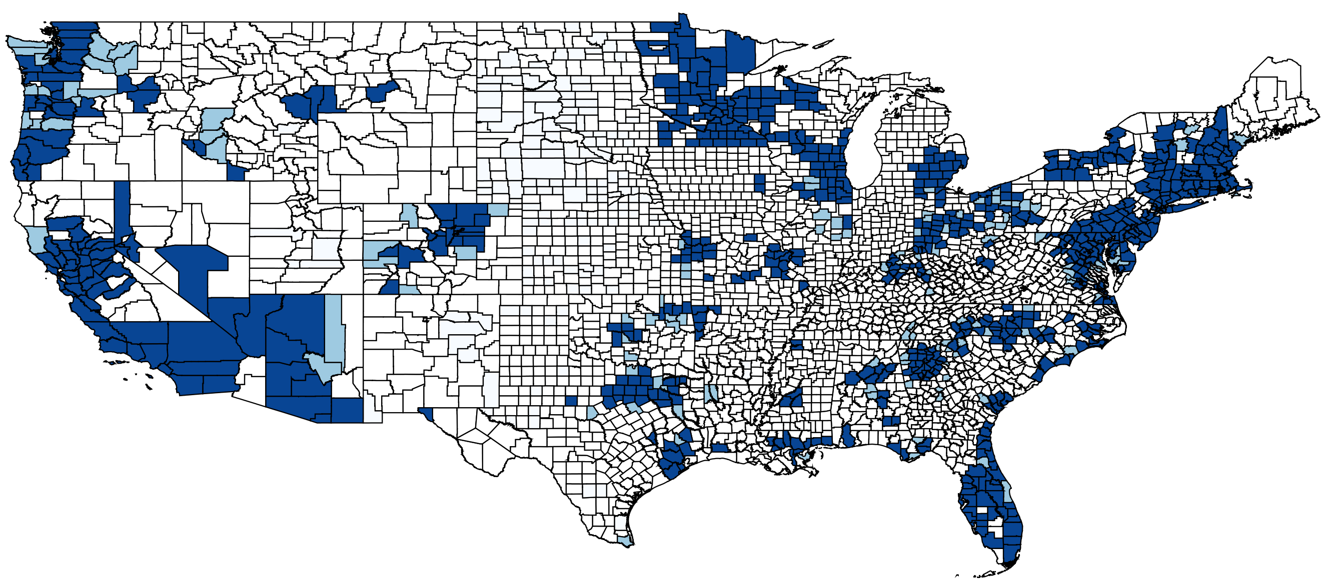
Note: Dots represent the index and year-over-year price changes for the entire U.S. for only the month of November for the designated year.
Source: Multiple Listing Service data provided by CoreLogic and FHFA HPI® (purchase-only, not seasonally adjusted).

Figure 10: Counties with Listings Between 2000 - 2021



Note: Data is presented after culling for outliers.
Source: Multiple Listings Service data provided by CoreLogic.

Figure 11: Counties with Any Index, 2000 - 2021



Note: Filled in counties are those for which any index could be calculated and darker counties are those for which an advanced index could be calculated.
Source: Multiple Listings Service data provided by CoreLogic.