Can Stay-at-Home Orders Create a Housing Boom? *

Alina Arefeva
University of Wisconsin-Madison

Shengwei Guo
University of Hong Kong

Lu Han
University of Wisconsin-Madison

Victor Ortego-Marti
University of California-Riverside

September 4, 2025

Abstract

We examine the impact of stay-at-home (SAH) orders on housing markets through the lens of a search-theoretic framework. By restricting in-person searches, SAH orders created a natural experiment to assess how temporary disruptions to search technology influence housing outcomes. We find prices rose while sale hazard, sales, and listings declined, particularly in neighborhoods with more search frictions proxied by older housing and lower internet penetration. A random matching model with heterogeneous buyers explains these patterns, showing that SAH-induced delays shifted the buyer pool toward more motivated buyers, leading to higher prices and lower liquidity even after SAH orders were lifted.

Keywords: housing, liquidity, search and matching, pandemic-era policies

JEL Codes: C78, R10, R21, R31, D83

*Arefeva: arefeva@wisc.edu, 975 University Ave, Grainger Hall 5259, Madison, WI, 53706, USA, Guo: swguo@hku.hk, Han: lu.han@wisc.edu, Ortego-Marti: victorom@ucr.edu. We thank Dayin Zhang and Dimitris Friesen for geocoding CoreLogic data. Danny Edgel, Sharada G Dharmasankar, and Congyan Han provided excellent research assistance. The paper has also benefited from the feedback of our discussants Xue Xiao, Qi Li, Walter D'Lima, N Vera Chau, of workshop participants at the AEA Annual meetings, the Costa Rica Search and Matching Conference, the West Cost Search and Matching Group Spring Workshop at the Federal Reserve Bank San Francisco, the AREUEA National Conference, the "Search in Housing Markets" Conference at the Imperial College London, the UEA Conference, the Zurich-Bern Real Estate and Finance Economics Workshop, and seminar participants at the National University of Singapore, Monash University and the University of Melbourne. Alina Arefeva and Lu Han gratefully acknowledge financial support from the Wisconsin Alumni Research Foundation, and the latter also from the Social Sciences and Humanities Research Council of Canada. All errors are our own.

1 Introduction

The Covid-19 pandemic and the measures implemented to limit the virus's spread caused widespread disruption across economic sectors, creating a unique natural experiment for studying market behavior. A growing literature has leveraged this shock to examine its effects across various settings, including stock returns (Fahlenbrach, Rageth, and Stulz (2021)), financial markets and the real economy (Goldstein, Koijen, and Mueller (2021)), mutual funds (Ma, Xiao, and Zeng (2022)), banks (Levine, Lin, Tai, and Xie (2021)), consumer spending (Goolsbee and Syverson (2021)), and preference shifts across locations and segments (Liu and Su (2021); D'Lima, Lopez, and Pradhan (2022); Gupta, Mittal, Peeters, and Van Nieuwerburgh (2022)).

Yet, despite housing being the largest asset for most households, a key driver of macroeconomic activity, and with search playing a fundamental role in the transaction process, little is known about how the market responded to pandemic-era disruptions to home search – particularly those caused by Stay-at-Home (SAH) orders. Implemented in 2020, these orders sharply curtailed in-person activity and disrupted traditional home-search channels, which depend heavily on property visits and neighborhood exploration. Surprisingly, during this period, house prices rose even as foot traffic collapsed (Figure 1). This surge in prices, alongside declining buyer traffic, presents a puzzle: home search is costly; with much-interrupted search activities under SAH, one would expect that housing markets would come to a halt – yet prices surged instead.

In this paper, we estimate the causal effects of Stay-at-Home (SAH) orders on the U.S. housing market and interpret our findings through a search-theoretic framework in which SAH orders represent an exogenous decline in search efficiency. Using unusually rich transaction-level data from the U.S. housing market, our analysis reveals two novel findings.

First, all else equal, the implementation of the SAH order led to the following shifts in housing market dynamics during the SAH period: sale prices rose by 3%, the sales hazard declined by half, and both transactions and listings fell sharply, by 19% and 30%, respectively.[1] These findings point to disrupted search processes as the primary driver of price growth. Intuitively, a drop in search efficiency increases the expected sellers' time-on-the-market, raising the cost of listing a home and requiring a higher price to incentivize seller entry. Simultaenously, it becomes more difficult for buyers to find another match, raising the value of successful matches and increase buyers' williness to pay. Together, these lead to an increase in sales price, along with reduced sales hazard, transactions and listings. We formalize this mechanism in a random matching model with Nash bargaining and free entry of sellers.

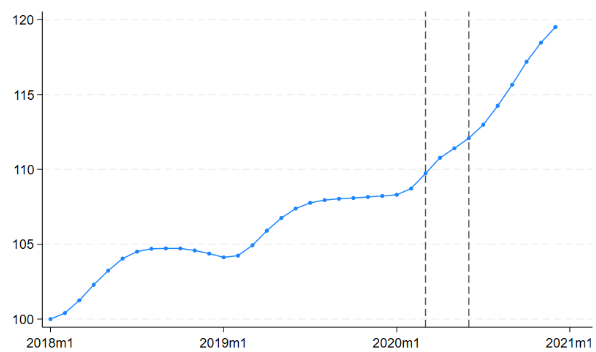
Second, after SAH orders are lifted, listings and transactions climb back, while the increase in prices and the decline in the sales hazard persisted." These post-SAH dynamics are difficult to reconcile with a frictionless model, but are consistent with an extended search framework featuring heterogeneous buyers. In particular, search disruptions during the SAH period slow the matching process and gradually shift the composition of the buyer pool: buyers who remain in the market despite prolonged search become increasingly motivated and tend to have a higher willingness to pay. When restrictions are lifted, this backlog of high-valuation buyers re-enters an inventory-constrained market, sustaining elevated prices and continued low sales hazard.

Together, these findings underscore the need for a general equilibrium framework that explicitly incorporates frictions in the search and matching process to understand the effects of SAH orders. As detailed later, our empirical design leverages rich variation across housing units and neighborhoods at a granular level. Importantly, we show that the estimated effects cannot be explained solely by temporary demand

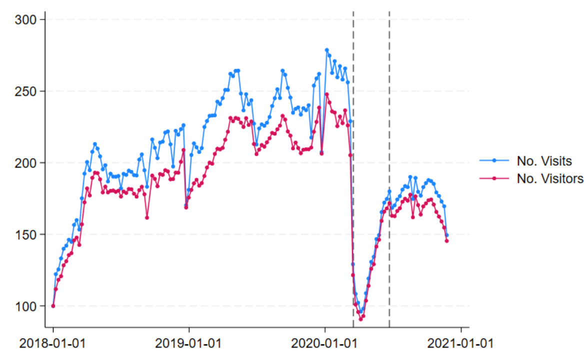
[1] The sales hazard is a dummy variable equal to 1 if a sales contract was signed on a specific date for a given listing. We use the sales contract date rather than the closing date to avoid delays associated with post-contract closing processes.

or supply shocks during the SAH period, independent of search frictions. For instance, a demand shock might account for rising prices but would also predict an increase in listings and sales, which we do not observe. Likewise, a supply shock would suggest a higher sales hazard, which is inconsistent with our results. Even a combination of demand and supply shocks cannot explain the persistence of elevated prices and low sales hazard after the SAH period. Our findings point to the central role of search frictions in shaping housing market dynamics.

Figure 1: Case-Shiller House Price Index and Foot Traffic



(a) National Case-Shiller House Price Index



(b) Foot Traffic from SafeGraph (2025) Data

Notes: 1) Vertical lines show the earliest start of the stay-at-home order on March 17, 2020, and the latest end of the stay-at-home order on June 22, 2020. 2) All series are normalized to 100 in January of 2018 when the SafeGraph data starts.

Our analysis begins by leveraging CoreLogic's comprehensive dataset of individual residential property transactions between 2017 and 2022, covering the entire U.S. market. The dataset combines owner transfer records, historical tax assessments, and multiple listing service (MLS) data, offering unusually rich information on house characteristics and transaction history. To identify the effects of SAH orders, we exploit their staggered rollout across counties, illustrated in Figure 2, using a border group differences-in-differences design. Specifically, we compare adjacent neighborhoods on either side of a county border, where one was subject to SAH orders and the other was not, but both share similar housing stock and neighborhood characteristics at a fine geographic level. This approach allows us to account for unobserved local heterogeneity and is supported by strong evidence of parallel pre-trends across all key housing market outcomes.

We further strengthen identification by incorporating a rich set of controls and high-dimensional fixed effects. For the sales price and sales hazard estimations, we include detailed property- and neighborhood-level characteristics along with census tract fixed effects; for daily sales and listing outcomes, we add tract-by-year-month fixed effects to capture changes in housing stock composition over time at the neighborhood level. Additionally, we control for daily county-level COVID-19 infection rates to account for evolving health risks, and for distance to the central business district (CBD) to capture differences between urban core and suburban areas.

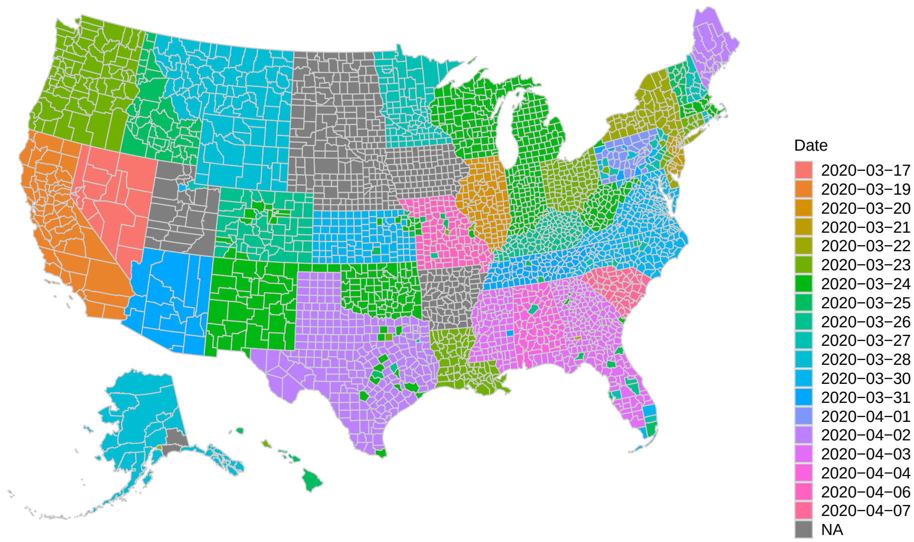
We find that SAH orders had large and persistent effects on housing market dynamics. During the SAH period, home prices rose, the sales hazard declined sharply, and both sales and listings dropped significantly. After SAH orders were lifted, sales and listings rebounded, but prices remained elevated and the sales hazard stayed low. These patterns suggest that the impact of SAH orders extended well beyond the policy window, triggering a sustained housing market boom. The results are robust across a wide range of specifications,[2] additional controls, and broader geographic samples.[3] To validate our design, we further conduct placebo tests using pre-pandemic years and randomly assigned SAH dates, both of which yield null results — confirming that our estimates are driven by the actual timing of policy implementation.

Importantly, the effects of SAH orders are significantly amplified in markets with greater search frictions. Using tract-level measures – Internet penetration and the share of older homes – we find that price increases and declines in sales hazard and transaction volume are much stronger in areas with limited online access and older

[2]This includes an alternative donut-hole approach, which helps address potential concerns about demand spillovers across the border.

[3]We extend the estimation sample from within 2 miles of the border to 5 and 10 miles, and find that the estimated patterns hold for both the border sample and the broader city sample.

Figure 2: Start Dates of the Stay-at-Home Orders Across U.S. Counties



housing stock, where in-person search is more essential. These results underscore the role of search frictions in magnifying the impact of temporary disruptions and highlight the relevance of a search-theoretic framework for interpreting housing market responses and informing policy.

We then develop a search model that incorporates the economic forces highlighted by these new findings to better understand the housing market effects of a generic decline in search efficiency, such as that introduced by SAH orders. The model features random matching, Nash bargaining, and free entry of sellers. In this framework, an exogenous drop in search efficiency reduces the probability that a home sells, i.e., the sale hazard. In a frictionless market, such a slowdown would prolong time on the market and reduces sales, but it would not affect prices. However, in the presence of search frictions, reduced search efficiency increases the equilibrium price through two distinct channels. First, sellers facing longer expected time on the market and higher holding costs require higher prices to be incentivized to enter. Second, the value of a successful match rises for buyers, who face greater difficulty in finding alternatives, increasing their willingness to pay. Both mechanisms hinge on the presence of search frictions, which shape the value of outside options for buyers and sellers and hence their bargaining position.

In addition, lower search efficiency slows the matching process, leading to an accumulation of buyers actively searching at any given time and a shortage of new listings. These dynamics – rising prices, declining sales hazard, and falling listings – closely match the patterns we estimate in the data during the SAH period.

To rationalize the empirical findings after SAH orders are lifted, we extend our baseline model by introducing heterogeneity among buyers in the spirit of Albrecht et al. (2007). Buyers enter the housing market as relaxed buyers but, over time, become motivated buyers at a given rate, facing higher search costs. This assumption captures the idea that as buyers spend more time unsuccessfully searching, they grow more desperate, experiencing increasing costs associated with failing to secure a home. This mechanism leads to lasting effects of SAH orders through a compositional shift in the buyer pool. Since SAH orders prolong search durations, more buyers become motivated, increasing the overall prevalence of buyers with a higher value from matching. This shift in the buyer distribution takes time to adjust, sustaining elevated demand, higher price, and a lower sales hazard even after SAH orders are lifted – a pattern consistent with the empirical findings.

To conclude, our findings have novel and important implications. While SAH measures were intended to mitigate the spread of infection, their disruptions of home search process had unintended consequences of worsening housing affordability and availability, as reflected in higher prices, a lower sales hazard, and declines in both sales and listings. Further, the elevated prices and reduced sale hazard persist even after SAH orders are lifted, as buyers who were unable to find homes during the SAH period become more desperate to purchase afterward. These effects are well captured by a random matching model where SAH reduces search efficiency. Moreover, our evidence on the decline in the sales hazard and the heterogeneous effects of SAH on housing market with varying levels of Internet penetration and housing age demonstrate that SAH orders do not affect the housing market on their own; rather, they interact with search frictions when shaping market dynamics. Thus, a careful evaluation of such government interventions in the housing market must consider the role of search frictions.

Related literature Our study contributes to two major strands of recent literature. The first examines the impact of lockdowns on economic and social outcomes, including households' macroeconomic expectations (Coibion, Gorodnichenko, and Weber (2020)), employment (Baek, McCrory, Messer, and Mui (2021), Kapička and Rupert (2022), Jackson and Ortego-Marti (2024)), and commercial real estate markets (Ling, Wang, and Zhou (2020), Rosenthal, Strange, and Urrego (2022), Wang and Zhou (2023)). Financial economists have further explored its effects on corporate bond markets (Haddad, Moreira, and Muir (2021); Kargar, Lester, Lindsay, Liu, Weill, and Zúñiga (2021); O'Hara and Zhou (2021); Boyarchenko, Kovner, and Shachar (2022)), stock markets and returns (Fahlenbrach, Rageth, and Stulz (2021)), money market funds (Li, Li, Macchiavelli, and Zhou (2021)), banks (Acharya, Engle, Jager, and Steffen (2024)), and sovereign credit risk (Augustin, Sokolovski, Subrahmanyam, and Tomio (2022)).

Our work contributes to this literature by focusing on housing — the largest financial asset and consumption item for most American households. In this regard, our study relates to D'Lima et al. (2022), who estimate the heterogeneous pricing effects of shutdown orders based on factors such as population density, property size, and structural density. We take a novel approach by examining a previously unexplored dimension of Stay-at-Home (SAH) orders, i.e. their impact on the housing market through disruptions to search technology. As a result, our analysis extends beyond pricing effects to include a broader set of housing market outcomes (prices, sales hazard, listings, and transactions) and explores heterogeneity based on the degree of search frictions. The focus on search frictions also allows us to offer a general equilibrium framework to understand the mechanisms underlying homebuyers' and sellers' responses to interruptions in search technology, thereby rationalizing the observed price boom during and beyond the SAH period.

Our theoretical framework builds on a large body of literature examining the role of search frictions in the housing market. Since the seminal contributions of Arnott (1989) and Wheaton (1990), many studies have modeled housing search frictions using search and matching frameworks in the tradition of Diamond-Mortensen-Pissarides (Pissarides, 2000). Our work is most closely related to Albrecht et al. (2007). As in their paper, we introduce buyer heterogeneity and assume that buyers who search for longer periods of time become more desperate. Relative to their work, our model features a richer environment with a matching function, endogenous matching rates, and free entry of sellers, and we use this environment to study the effect of a drop in search efficiency on prices, sales hazard, listings, and vacancies. These features are important, because our composition mechanism relies on matching rates changing in response to SAH order. With constant matching rates this composition effect is absent. Other papers that assume a matching function to capture search frictions and free entry of sellers include Head et al. (2014, 2016), Garriga and Hedlund (2020) and Gabrovski and Ortego-Marti (2019, 2021, 2025).[4] Relative to papers in this literature, we introduce an environment with relaxed and motivated buyers, and a mechanism through which a shock to matching rates endogenously shifts the composition of buyers to analyze the effect of disruptions to search technology on housing markets.

While much of the housing search literature relies on a matching function to rep-

[4]Other papers that study the role of search frictions in the literature include Albrecht et al. (2016), Anenberg and Ringo (2024), Arefeva (2017), Burnside et al. (2016), Diaz and Jerez (2013), Guren (2018), Han et al. (2021), Kotova and Zhang (2020), Moen et al. (2021), Ngai and Tenreyro (2014), Ngai and Sheedy (2020, 2024), Novy-Marx (2009), Piazzesi et al. (2020), and Smith (2020). See Han and Strange (2015) for an early review of this literature.

resent search frictions, Genesove and Han (2012) and Badarinza et al. (2024) provide empirical evidence for these frictions and estimate matching functions for the housing market. In a similar spirit to Badarinza et al. (2024), who estimates the effects of a "mini-budget" shock, our paper exploits a natural experiment created by SAH orders. This enables us to be among the first to estimate how shocks to search technology influence housing market outcomes. We interpret these effects through a search-theoretic framework that highlights the key trade-offs faced by buyers and sellers. In this regard, our work is also consistent with Han et al. (2021) and Han et al. (2025).

2 Data

To examine the impact of Stay-at-Home (SAH) orders on housing market dynamics, we use three detailed micro-level housing datasets from CoreLogic, covering 2017 to early 2022. Before detailing our variable construction, we first describe the datasets and the data cleaning process.

2.1 CoreLogic Owner Transfers

Our primary source for the transaction level sample transactions is the CoreLogic Owner Transfer dataset, which provides detailed sales transaction information, including sale date, price, property location, buyer and seller details, type of sale, and deed type. After applying several data accuracy filters,[5] the cleaned dataset retains 28% of the original raw data. To further refine the sample, we exclude resales of the same property within a year to eliminate home flipping activity, reducing the dataset

[5] From the CoreLogic Owner Transfer dataset, we apply the following filters: (1) Remove observations with missing sale dates or unverified addresses; (2) Exclude foreclosures, real estate-owned (REO) sales, and inter-family transfers; (3) Retain only deed and quitclaim transfers, excluding mortgage releases, judgments, mechanic liens, lis pendens, notices of default, loan assignments, deeds of trust, and foreclosures; (4) Exclude exchanges, lease agreements, multi-parcel transactions, parcel splits, and mobile home sales, as their prices do not accurately reflect land and improvement values; (5) Remove unconfirmed transactions and non-residential land uses.

by an additional 2.2%.

2.2 CoreLogic Tax Assessments

We supplement transaction data with house characteristics from the CoreLogic Tax Assessment dataset, including age, age squared, log of the square footage of the living area, log of the lot size, dummies for the number of bedrooms, and dummies for the number of bathrooms, categorical variables for the condition of the property, type of heating, type of air conditioning, property type (single family, multi-family, etc.), number of garage spaces, number of fireplaces and a dummy variable indicating whether the property is newly constructed.

To clean the tax assessment data, we applied a series of filters, resulting in a dataset that retains 63% of the raw data.[6] To address missing tax years, we use correspondences between tax roll edition numbers and tax years within the same county. Finally, we merge the tax assessment data with transaction records using CoreLogic's unique property identifier, ensuring sales are linked to the most recent tax assessment.

2.3 CoreLogic MLS

We also use CoreLogic Multiple Listing Service (MLS) data, which provides detailed property listings, including listing date, contract date, sale closing date, listing price, price adjustments, house characteristics, and listing status (withdrawn, expired, or sold). To clean the MLS data, we applied a series of filters, resulting in a final dataset

[6]From the CoreLogic Tax Assessment dataset, we apply the following filters: (1) Exclude properties with multiple units or buildings to ensure consistency in our sales price analysis, reducing the dataset by 6%; (2) Retain only residential properties, including single-family residences, condominiums, duplexes, triplexes, and apartments, while excluding commercial, industrial, and other non-residential properties, removing 30% of raw observations; (3) Remove properties in the foreclosure process, further reducing the dataset by 1.2%.

that retains 73% of the raw listings.[7] To ensure accuracy, we account for re-listings using the methodology in Garriga and Hedlund (2020), which corrects for repeated postings of the same property.

The coverage of the MLS data increases over time and varies by county. To account for this, we follow Anenberg and Ringo (2024) when imputing the number of new listings. Specifically, we exclude counties that meet any of the following criteria: (1) the absolute value of the annual sales growth rate exceeds 75%, (2) the number of sales in any single year is fewer than 10 or totals less than 400 over the period from 2008 to 2021, or (3) the average number of observations per year is less than one. For statistics involving the contract date, such as the number of newly pending listings, we exclude counties where contract data is missing for at least 2% of sales in any year.

Finally, we apply additional restrictions to the transaction sample by excluding: (1) properties in the top 1% of land size, living area, bedroom count, and bathroom count distributions, as well as those built before 1800 or after 2023; (2) properties with missing sale prices or those in the top/bottom 1% of county-level price distributions. For the listing sample, we remove listings that remained on the market for more than four years or where the contract date predates the listing date.

After applying all these filters, we obtain a refined dataset that ensures accuracy and consistency across transactions, listings, and house characteristics, making it well-suited for analyzing the effects of SAH orders on housing market dynamics.

[7]From the CoreLogic MLS data, we apply the following filters: (1) Exclude non-sale listings, removing 11% of the original dataset; (2) Exclude listings associated with foreclosures (1%), REO sales (3%), and short sales (3%); (3) Remove commercial, industrial, farm properties, boat docks, vacant land, mobile homes, fractional ownership, and timeshares, eliminating 9% of listings.

2.4 Outcome Variables Construction

Our analysis focuses on sales prices, sale hazard rates, transaction volumes, and new listings. Sales price data are drawn from the CoreLogic Owner Transfer dataset.

Following Gerardi et al. (2023), we construct the sale hazard by converting the listing-level sample into a daily panel dataset. A listing enters the sample on its listing date and exits either on its contract date if sold or on its last listing date if unsold. This setup allows us to precisely align listing activity with county-level SAH orders. We then create a sale indicator variable, which equals 1 on the contract date when a property is sold and 0 otherwise, allowing us to estimate the probability of sale at time t conditional on survival through $t-1$.

Using MLS data, we measure sales as the number of listings with signed contracts on a given day and new listings as those newly introduced to the market. Both measures are constructed at the census tract–by–day level, allowing for precise alignment with the timing of SAH policy implementation.

2.5 Supplementary Datasets

We supplement our CoreLogic data with several additional datasets. First, a property's exposure to COVID-19 risk may vary by its distance to downtown. To account for this, we add a control variable measuring the distance to the nearest Central Business District (CBD).[8]

Second, we incorporate county-level daily COVID-19 case data from Johns Hopkins. To control for infection rates, we calculate the daily number and growth rate of new COVID-19 cases within a county. The daily number of new cases is normalized by the county population.[9]

[8]This distance is calculated in two steps: (1) identifying the county's most populous urban area (Census Designated Place) as the county center, and (2) geocoding its coordinates using Google Maps, typically selecting the City Hall or the largest road intersection as the reference point. The shortest distance between a property and the nearest county center is used as its distance to downtown.

[9]The data source is `https://github.com/CSSEGISandData/COVID-19`. To remove potential

Third, we obtain data on the start and end dates of stay-at-home (SAH) orders from Johns Hopkins University, with manual updates based on Husch Blackwell and Mercury News.[10] We construct our final sample by merging CoreLogic data with neighborhood characteristics from the 2019 American Community Survey (ACS), COVID-19 infections data, and SAH order data at the census tract level.

Finally, using ACS data, we construct two census tract level variables to measure the degree of search frictions across neighborhoods: (1) the fraction of households with internet access, serving as a proxy for access to online search tools; and (2) the fraction of older homes, indicating a greater dependence on in-person inspections.

2.6 Summary Statistics

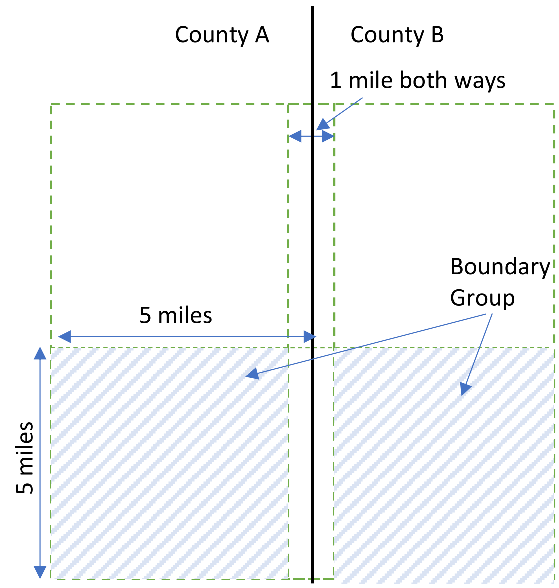
After merging the datasets, we narrow the sample down to the census tracts or properties within 1-5 miles from the county border to compare housing markets on either side of the county border, as we will discuss in Section 3. Our main results are based on this sample.

Tables 1 presents summary statistics for this sample for the dates of the SAHs, selected attributes of properties and neighborhoods, and housing market outcomes that we are studying. Panel A shows the summary statistics for the housing markets. The average sales price is around $360,000. The average size of the lot is 13,045 sq.ft., and the living area is 1,985 sq.ft. with 3 bedrooms and 1.8 bathrooms. The mean distance to the downtown is 22 miles. The average probability for a listing to accept a purchase offer at a given day, accounting for any potential relistings, is 1%. Panel B shows the average number of sales and listings in our border group by day sample with 0.1 sales/listings per day, which is an average of four new listings and three sales per month. Moreover, the daily sales/listings in the census tracts are zero

data entry errors, we replace (1) negative county-day observations with missing values, and (2) the top and bottom 0.1% of percent changes in new cases with missing values.

[10] `https://www.huschblackwell.com/` and `https://www.mercurynews.com`.

Figure 3: An Example of a Boundary Group



for more than 50% of samples, as can be seen from the median. It is expected for a sample of this high frequency and finer geography. This justifies the application of Poisson regression for these market-level variables.

Panel C shows the covariates from the ACS and infection variables. According to ACS, 87% of households have internet access, and 47% of housing units were built before 1970 (equivalent to a property age of more than 50 years during the COVID period) for an average tract. In addition, there are large variations in both covariates, as reflected by the large standard deviations.

Panel D shows the earliest and latest start and end dates of the SAHs as well as the mean time for the U.S. counties. In terms of the rollback date, the average county reopened in early May 2020, and there is about a 2-month difference between the county that ended the SAH order the earliest and the latest, which provides variations to identify the effects of the SAH rollback.

3 Empirical Strategy

The main empirical strategy resembles a variant of the regression discontinuity design, focusing on neighborhoods cross county borders where one county implemented an SAH order while the adjacent county did not. The possibility that housing market outcome variables make a discrete jump at the border while neighborhood demographics, economic conditions, and housing stock composition continue to change in a smooth manner allows the relationship between the SAH and housing market outcomes to be isolated.

To ensure the housing stock and neighborhoods are relatively homogeneous, we construct boundary groups around such county borders, following Han, Hatfield, and Hong (2023). To construct a boundary group, we start 1 mile away from the county border and extend the area by $x = 2, 5, 10$ miles from the border, creating bands that are 1, 4, and 9 miles wide, respectively. These bands are then divided into equally sized groups, each $x = 2, 5, 10$ miles tall. Figure 3 provides an example of a 1–5 mile boundary group used for our benchmark results. The black solid line represents the county border, and a boundary group consists of shaded areas comprising two rectangles on either side of the border, each 5 miles tall and 4 miles wide. We exclude properties within 1 mile of the border to minimize cross-border spillovers. The boundary groups are designed to be small enough to ensure similar neighborhoods on either side of the border, yet large enough to include sufficient observations to estimate the effect of a stay-at-home order. We conduct the empirical analysis at both the market segment level and the transaction/listing level.

Market Segment Level. A market segment is defined as a census tract $\times$ year $\times$ month $\times$ day.[11] To analyze the effects of SAH orders on sales and listings, we estimate

[11]We include census tracts whose centroids are located within the boundary groups, excluding those spanning multiple boundary groups.

the following equation:

$$Y_{rt} = \alpha_t + \beta_U \text{underSAH}_{ct} + \beta_A \text{afterSAH}_{ct} + \text{Inf}_{ct}\beta_I + \xi_c + \zeta_{cc'} + \psi_g + \omega_r + \varepsilon_{rt}, \quad (1)$$

where r is the census tract, t represents the day, g is the boundary group, c is the county, and c' is the neighboring county. The model includes year-month fixed effects (α_t), county fixed effects (ξ_c), county border/boundary fixed effects ($\zeta_{cc'}$), boundary group fixed effects (ψ_g), and census tract fixed effects (ω_r).[12] In addition, we control for the distance to the Central Business District (CBD) and the infection measures, Inf_{ct}, adjusted to account for the lag between contract signing and closing. Specifically, we use the mean daily infection rate and the percentage change from the prior month.

The treatment variables include underSAHct, which equals 1 if a stay-at-home order is active in county c on day t, and 0 otherwise; and afterSAHct, which equals 1 if the stay-at-home order has ended in county c by day t, and 0 otherwise.

The dependent variable, Y_{rt}, is either the number of sold homes or new listings. For finer market segments, such as Census-tract-day in our setting, a challenge arises when the number of sales or listings is zero. To address this challenge, one common approach in the previous literature is to use log transformation $\log(1+Y)$. However, recent studies have shown that the estimated coefficients using this approach should not be interpreted as percentage changes (Cohn, Liu, and Wardlaw (2022) and Chen and Roth (2023)). Thus, following Cohn, Liu, and Wardlaw (2022), we employ Poisson regression for these count-like variables.

Transaction/Listing Level. At the transaction/listing level, the outcome variables include the sales price and the sale hazard. To study the SAH effects on these

[12] A county border consists of a collection of smaller boundary groups, as shown in Figure 3.

outcomes, we estimate:

$$
\begin{aligned}
Y_{it} = \alpha_t + \beta_U \textbf{underSAH}_{ct} + \beta_A \textbf{afterSAH}_{ct} + \textbf{Inf}_{ct}\beta_I + \\
+ H_i\beta_H + \xi_c + \zeta_{cc'} + \psi_g + \omega_r + \varepsilon_{it},
\end{aligned} \tag{2}
$$

where Y_{it} represents the outcome variable for property i on day t, such as the logarithm of the sales price or a binary indicator equal to 1 on the sales contract date and 0 otherwise.[13] In addition to the controls included in equation (1), we incorporate a vector of time-varying property-level characteristics, H_{it}, as described in Section 2.2.

Identification Assumptions. The main challenge in identifying the SAH effect is the possible correlation between the implementation of SAH and unobserved neighborhood or property characteristics. For example, properties in denser neighborhoods may have been more affected by COVID-19, prompting earlier adoption of SAH orders. Additionally, during the pandemic, buyers may have shown a stronger preference for larger homes and properties located farther from dense urban centers (Gamber et al., 2023; Gupta et al., 2022; Liu and Su, 2021; Ramani and Bloom, 2021; Kim et al., 2023). In both cases, the estimated SAH effects could be biased.

Our empirical strategy addresses these concerns by combining a differences-in-differences framework with a border group design, which allows for comparisons between adjacent neighborhoods that share relatively homogeneous housing stock and neighborhood characteristics at a granular geographic level. This approach is supplemented with a rich and flexible set of controls and fixed effects. Specifically, we include detailed property-level characteristics and census tract fixed effects in the sales price and sales hazard estimations, and tract-by-year-month fixed effects in the estimation of daily sales and listings to account for variation in housing composition. Additionally, we control for COVID-19 infection rates to address potential endogene-

[13]We use a linear probability model to estimate the effect of SAH orders on the sale hazard, as it offers greater flexibility in incorporating granular fixed effects.

ity in the timing and implementation of SAH orders.

Note that for identification, we do not require house characteristics to be identical across the county border. Rather, our strategy relies on the assumption that any cross-sectional differences in house characteristics between adjacent neighborhoods, if they exist, remain stable over time. To assess this, we examine whether differences in home characteristics between neighborhoods on either side of the county border change meaningfully during or after the SAH period. Appendix Table A4 shows no noticeable shifts in cross-sectional differences for most observed characteristics when we control for year-by-month, border group, and border fixed effects as in our main analysis. Given this stability, it is unlikely that unobserved house characteristics would exhibit meaningful shifts either. This allows us to difference out cross-sectional differences in housing and neighborhood conditions.

Formally, we impose the conditional parallel trends assumption. To state this assumption, let $Y_{it}(1)$ be the outcome that tract or house i would experience in time period t if it became treated (underSAH$_{it}$ =1). Denote the outcome that tract or house i would experience in time period t if it was not treated as $Y_{it}(0)$. Put together all covariates we use in the corresponding regressions in equations (1) and (2) in one matrix X.

Using this notation, we can state the conditional parallel trends assumption: trends in untreated tracts or houses are the same for treated units as if they were not treated, conditional on the covariates X: $\mathbf{E}[\Delta Y_{it}(0)|X, \textbf{underSAH}_{it} = 1] = \mathbf{E}[\Delta Y_{it}(0)|X,$ underSAH$_{it} = 0]$. We provide evidence in Section 4.2 that the conditional parallel trend assumption holds by showing that the event-study coefficients prior to the SAH treatment are insignificant.

Table 1: Summary Statistics

	Panel A: Transaction Level Variables				
	Mean	Median	SD	Min	Max
Sale Price, $	359,980	280,000	347,843	1,500	15,750,000
Land Size, sq.ft.	13,045	7,405	36,246	1	596,360
Living Area, sq.ft.	1,985	1,708	1,016	2	6,804
Year Built	1,969	1,972	28	1,800	2,021
Number of Bedrooms	3.06	3.00	0.83	1.00	6.00
Number of Bathrooms	1.77	2.00	0.94	0.00	4.50
Distance to CBD: City Hall, miles	21.71	8.96	55.49	0.03	452.10
Observations			511,390		
Dummy: Sale	0.01	0.00	0.12	0.00	1.00
Observations			18,246,055		
	Panel B: Market Level Variables				
Sales, per day	0.11	0.00	0.36	0.00	73.00
Observations			3,296,298		
New Listings, per day	0.14	0.00	0.41	0.00	73.00
Observations			3,594,851		
	Panel C: Neighborhood and Infection Variables				
Households with Internet Access, %	87.35	89.82	9.60	43.35	100.00
Housing Units Built Before 1970, %	47.26	49.50	33.62	0.00	100.00
Daily New Infections Per Capita	0.01	0.00	0.03	0.00	1.08
Percent Increase in Infections, %	4.87	0.00	95.26	-100.00	4,816.67
Observations			3,296,298		
	Panel D: County-level Stay-at-Home Order				
	Mean		Min		Max
SAH Start Date	03/28/2020		03/17/2020		04/07/2020
SAH Rollback Date	05/09/2020		04/13/2020		06/22/2020
Observations			3,142		

Notes: 1) The table reports the summary statistics for the main estimation samples. The main estimation samples include properties in the boundary groups that are within 1 to 5 miles of the county border. 2) The sales price is from the CoreLogic Deeds data; the dummy variable indicating whether a sales contract was signed on a specific date, the number of sales, and new listings per day are measured using the CoreLogic MLS data; the house characteristics are from the CoreLogic tax assessments data. Distance to CBD is the distance to the downtown from this property. 3) The fractions of housing units built before 1970 and households with internet access are from the 2019 tract-level American Community Survey, the infection data and the stay-at-home orders data are from Johns Hopkins University 4) Panel C presents summary statistics of the neighborhood and infection characteristics from the sales sample in Panel B. The summary statistics for the listings sample are similar.

4 Empirical Results

In this section, we present evidence on how SAH affects housing market activities and how these effects change over time and across neighborhoods.

4.1 Baseline Estimates

We begin by presenting our baseline estimates for sales price and sale hazard at the transaction/listing level, based on (2), using properties located in tracts within 1–5 miles of the county border.

Sales Prices and Sale Hazard. Panel A of Table 2 reports the estimated effects of stay-at-home (SAH) orders on sales prices. Column (1) includes standard controls, including house characteristics as detailed in Section 2.2, distance to the CBD, infection rates, year × month fixed effects, and county fixed effects. The results indicate a strong, statistically significant increase in sales prices during the SAH period, with the effect persisting afterward.

To further account for neighborhood conditions, we progressively introduce more granular fixed effects across specifications. Column (2) adds county-border fixed effects, and Column (3) includes border group-specific fixed effects. In our most demanding specification, shown in Column (4), we replace county fixed effects with both boundary group and tract fixed effects. This specification compares properties in pairs of adjacent neighborhoods located on opposite sides of a county border – one subject to the SAH order and the other not – as illustrated in Figure 3. This helps ensure greater comparability in housing stock and neighborhood characteristics, even along unobserved dimension. The estimated effects of the SAH order on sales prices remain consistent and stable across specifications, underscoring the strength of our property- and neighborhood-level controls. In particular, sales prices increased by approximately 3.5% during the SAH period relative to pre-pandemic levels, and this

Table 2: Sales Prices and Sale Hazard

	(1)	(2)	(3)	(4)	(5)
	Panel A: Sales Price				
Under SAH	0.042***	0.032***	0.029***	0.035***	0.039***
	(0.010)	(0.010)	(0.009)	(0.008)	(0.007)
After SAH	0.038***	0.035***	0.034***	0.043***	0.047***
	(0.007)	(0.006)	(0.006)	(0.005)	(0.005)
Observations	511,457	511,457	511,457	511,415	510,693
R-squared	0.746	0.768	0.786	0.850	0.860
	Panel B: Sale Hazard				
Under SAH	-0.005***	-0.005***	-0.005***	-0.005***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
After SAH	-0.005***	-0.005***	-0.005***	-0.005***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	18,246,058	18,246,058	18,246,058	18,246,055	17,012,952
R-squared	0.007	0.007	0.008	0.008	0.009
House characteristics	Y	Y	Y	Y	Y
Month x Year FE	Y	Y	Y	Y	Y
Infections	Y	Y	Y	Y	Y
Assessment value	N	N	N	N	Y
County FE	Y	Y	Y	N	N
Tract FE	N	N	N	Y	Y
Boundary FE	N	Y	Y	Y	Y
Border Group FE	N	N	Y	Y	Y

Notes: 1) The table reports results for the sample of residential properties within 1-5 miles of the county border that were sold or listed between 2017 and early 2022. 2) The dependent variables are the logarithm of the sales price in Panel A and a dummy variable that takes a value of 1 at the sales contract date and zero otherwise in Panel B. 3) The house characteristics include distance to the Central Business District, age, age squared, log of the square footage of the living area, log of the lot size, dummies for the number of bedrooms, dummies for the number of bathrooms, categorical variables for the condition of the property, type of heating, type of air conditioning, property type, number of garage spaces, number of fireplaces, and a dummy variable indicating whether the property is newly constructed. 4) The infection variables include the number of new infections per capita and the percent change in new infections. 5) ***, **, and * denote significance at the 1%, 5%, and 10% levels.

effect persists even after the SAH period ends.

To address the possibility that observed house characteristics may not fully capture time-varying, unobserved housing quality, we also control for time-varying tax assessment values, which may more comprehensively reflect property conditions (Han and Hong, 2024). As shown in Column (5), the estimates remain consistent with those in Column (4). This consistency is expected, as the inclusion of border group fixed effects ensures that comparisons are made between adjacent neighborhoods with similar housing conditions, and any residual differences are likely time-invariant, as supported in Table A4, and thus differenced out. However, because assessment values may absorb variation in sales prices that is informative for identification, we focus our discussion on the estimates in Column (4) going forward.

Turning to sale hazard, Panel B of Table 2 shows that, conditional on being listed, sellers were 0.5 percentage points less likely to sell their homes during the SAH period compared to pre-pandemic levels. Given that the average daily sale probability for a listing is 1%, this represents a 50% drop in sales likelihood during SAH. Similar to sales prices, the impact on sale hazard remains strong even after the SAH orders are lifted.

Sales and Listings. Table 3 presents the effects of SAH orders on sales and listings, measured at the tract-year-month-day level. Columns (1)–(4) replicate the specifications from Table 2, except that we no longer include property-level house characteristics. These characteristics are difficult to assign to market-segment-level observations, particularly for segments with zero sales or listings. However, the border-group design in column (4) ensures comparisons between adjacent neighborhoods with relatively homogeneous housing stock and neighborhood conditions. The estimates are remarkably consistent across specifications in both magnitude and statistical significance.

To further account for differences in housing composition, Column (5) includes

Table 3: Sales and Listings

	(1)	(2)	(3)	(4)	(5)
	Panel A: Sales				
Under SAH	-0.187***	-0.187***	-0.187***	-0.187***	-0.320***
	(0.032)	(0.032)	(0.032)	(0.032)	(0.041)
After SAH	-0.039	-0.039	-0.039	-0.039	-0.180***
	(0.035)	(0.035)	(0.034)	(0.034)	(0.055)
Observations	3,340,806	3,340,806	3,340,806	3,296,298	2,544,576
	Panel B: New Listings				
Under SAH	-0.300***	-0.300***	-0.300***	-0.300***	-0.433***
	(0.029)	(0.029)	(0.028)	(0.028)	(0.035)
After SAH	-0.149***	-0.149***	-0.149***	-0.149***	-0.344***
	(0.032)	(0.032)	(0.032)	(0.031)	(0.049)
Observations	3,622,786	3,622,786	3,622,786	3,594,851	2,933,076
Year x Month FE	Y	Y	Y	Y	N
Infections	Y	Y	Y	Y	Y
County FE	Y	Y	Y	N	N
Boundary FE	N	Y	Y	Y	Y
Boundary Group FE	N	N	Y	Y	Y
Tract FE	N	N	N	Y	N
Tract x Year x Month FE	N	N	N	N	Y

Notes: 1) The table reports results for the sample of residential properties within 1-5 miles of the county border that were sold or listed between 2017 and early 2022. 2) The dependent variables are the number of sales in Panel A, defined using the sales contract date, and the number of new listings in Panel B, defined using the first listing date. Both variables are calculated using the MLS sample and are measured at the census tract-by-day level. 3) The table shows the estimates from the Poisson pseudo-maximum likelihood regressions. 4) The infection variables include the number of new infections per capita and the percent change in new infections. 5) R-squared is not reported for the Poisson pseudo-maximum likelihood regressions because they are nonlinear so the residuals and predictions are not orthogonal. 6) ***, **, and * denote significance at the 1%, 5%, and 10% levels.

tract-by-year-month fixed effects, which control for time-varying variation in the types of homes transacted within each tract. While this specification reduces the sample size by nearly 20%, the estimates remain robust to this additional control.

Panel A shows that sales declined by 19% during the SAH period, with most of this effect dissipating after the SAH ended. Panel B indicates that new listings dropped by 30% under SAH, though the impact decreased by half after SAH orders were lifted. Further, the Wald test rejects the null hypothesis that the coefficients for the Under SAH and After SAH dummies are equal, with a p-value < 0.01 for both sales and listings, confirming that both sales and listings rebounded after SAH ended. While sales recovered relatively quickly, new listings rebounded more gradually after the SAH.

Thus far, our estimates are based on transactions occurring within 1–5 miles of the county border. A potential concern with this border design approach is that the estimated SAH effects might be driven primarily by neighborhoods located very close to the border. First, note that our specifications already control for distance to the central business district (CBD). In addition, Table A3 in the Appendix extends the column (4) estimates from Tables 2 and 3 to alternative samples, including properties within 1–2 miles and 1–10 miles of the border. The results remain consistent across these samples,[14] suggesting that the SAH effects apply more broadly across the city.

Given our comprehensive controls and the robustness of the estimates, column (4) in Tables 2 and 3, based on properties within 1–5 miles on either side of the border, is retained as the main specification moving forward. This approach strikes a balance by preserving sufficient variation while maintaining the relative homogeneity of the underlying estimation sample, thereby ensuring cleaner identification.

Placebo Tests. To further validate our empirical strategy, we conduct two placebo

[14]Although the SAH effects on prices and sales hazard are statistically insignificant in the 1–2 mile sample, the coefficient signs are directionally consistent with the other estimates. This insignificance is primarily due to the smaller sample size, as transactions in the 1–2 mile group comprise only about 5% of those in the 1–5 mile sample.

tests, with results summarized in Table A5 in the Appendix.

First, we re-estimate our main specifications assuming the SAH orders occurred in 2018 or 2019. Specifically, we redefine the SAH start and end dates to align with the same calendar dates as in 2020 but shift them to 2018 and 2019, respectively. Columns (1) and (2) show the results using the full sample, while Columns (3) and (4) restrict the sample to pre-2020 data. None of these placebo specifications replicate the patterns we observe in the actual data—namely, rising sales prices and sale hazards alongside declines in sales volume and new listings—lending support to the interpretation that the observed effects are unique to the time period during and after the SAH orders.

Second, we conduct a placebo test in which the SAH dates are randomly drawn from the empirical distribution of observed SAH dates across counties. Using these randomly assigned dates, we redefine the SAH indicators and re-estimate equations (1) and (2). We repeat this process 1000 times to obtain standard errors. Column (5) of Table A5 shows that the housing market outcomes do not systematically respond to these randomly assigned dates, suggesting that our results are indeed driven by the timing of actual SAH orders.

4.2 Dynamic Responses

Leveraging the rich dataset, we further explore the dynamic responses of the housing market to SAH orders using the 1–5 miles border sample. We extend regression (2) into the following specification:

$$\begin{aligned} Y_{igct} = \alpha_t + \sum_{k=-4}^{-2} \beta_k \textbf{underSAH}_{c,t+k} + \sum_{k=0}^{5} \beta_k \textbf{underSAH}_{c,t+k} \\ + \sum_{k=0}^{T} \beta_{k\text{After}} \textbf{afterSAH}_{c,t+k} + \textbf{Inf}_{ct}\beta_I + H_i\beta_H + \xi_c + \zeta_{cc'} + \psi_g + \varepsilon_{igcc't}, \end{aligned} \tag{3}$$

where $\beta_{-1} = 0$ is a normalization. Variables Y_{igct}, α_t, Inf_{ct}, H_i, ξ_c, $\zeta_{cc'}$, ψ_g are defined as in (1) and (2), and k represents a week.[15] Aggregating to a weekly level ensures sufficient transactions or listings in tracts within boundary groups to estimate dynamic effects, along with control variables and fixed effects.

Similarly, for sales and listings, we expand regression (1) as following:

$$\begin{aligned} Y_{gct} = \alpha_t &+ \sum_{k=-4}^{-2} \beta_k \textbf{underSAH}_{c,t+k} + \sum_{k=0}^{5} \beta_k \textbf{underSAH}_{c,t+k} \\ &+ \sum_{k=0}^{T} \beta_{k\text{After}} \textbf{afterSAH}_{c,t+k} + \text{Inf}_{ct}\beta_I + \xi_c + \zeta_{cc'} + \psi_g + \varepsilon_{igcc't}, \end{aligned} \tag{4}$$

where k is also defined as a week. β_k represents the average SAH effects at event time k relative to the baseline period ($k = -1$). Figures 4a, 4b, and 5a and 5b plot the estimated coefficients $\beta_{-4}, \ldots, \beta_5$ and $\beta_{0\text{After}}, \ldots \beta_{5+After}$ for prices, sale hazard, sales, and listings. Figure A1a further presents the corresponding estimates for sales and listings, controlling for tract-year-month fixed effects.

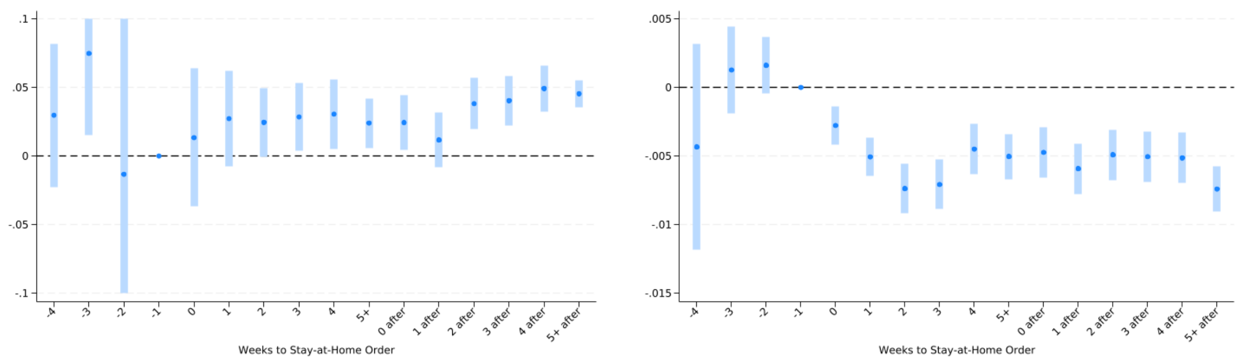
Before presenting the dynamic effects of SAH orders, it is important to note that for all housing outcome variables of interest, the pre-SAH coefficients are statistically insignificant in most pre-SAH periods. This supports the parallel trends assumption discussed in Section 3 and reinforces the validity of our identification strategy.

As shown in Figure 4, the implementation of SAH orders led to an immediate decline in sales hazard, which remained 0.05–0.1 percentage points below pre-pandemic levels throughout the SAH period. In contrast, sales prices showed a slight and statistically insignificant increase in the first week of the SAH period. However, starting from the second week, prices rose significantly and stabilized above pre-pandemic levels for the duration of the SAH period. This lagged price response aligns with the typical pattern in housing markets, where quantity adjustments precede price changes. Notably, the decline in sales hazard and the increase in prices persisted well beyond

[15]To prevent abuse of notations, ξ_c is replaced with census tract fixed effects for the analysis and results reported in all the following tables and figures.

Figure 4: Dynamic Effects on Prices and Sale Hazard

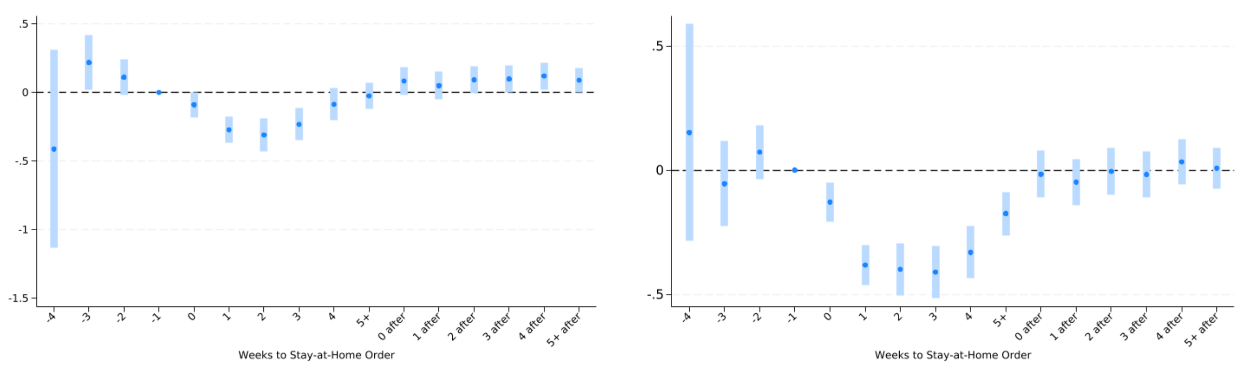
(a) Sales Price (b) Sale Hazard



Notes: 1) The panels show point estimates and 95% confidence intervals from even studies in (3). The period before the start of the SAH is the ommited period. 2) The figures report results for the sample of residential properties within 1-5 miles of the county border that were sold or listed between 2017 and early 2022. 3) The dependent variables are the logarithm of the sales price in figure (a) and a dummy variable that takes a value of 1 at the sales contract date and zero otherwise in figure (b). 4) The same house characteristics, distance to the CBD, and infection variables as in Table 2 are included as controls.

Figure 5: Dynamic Effects on Sales and Listings

(a) Sales (b) New Listings



Notes: 1) The panels show point estimates from the Poisson pseudo-maximum likelihood regression and 95% confidence intervals from event studies in (4). The period before the start of the SAH is the ommited period. 2) The figures report results for the sample of residential properties within 1-5 miles of the county border that were sold or listed between 2017 and early 2022. 3) The dependent variables are the number of sales in figure (a), defined using the sales contract date, and the number of new listings in figure (b), defined using the first listing date. Both variables are calculated using the MLS sample and are measured at the census tract-by-day level. 4) The same infection variables as in Table 3 are included as controls.

the SAH period, indicating that temporary interventions can have lasting effects on housing market dynamics.

Unlike sales price and sale hazard, the effects of SAH orders on sales and listings were mostly confined to the SAH period. As shown in Figures 5a and 5b, both sales and new listings declined sharply following the implementation of SAH orders, remaining below pre-pandemic levels throughout the SAH period. These declines peaked at 30% and 40%, respectively, during the second and third weeks under SAH. However, after the SAH period ended, both sales and new listings gradually climbed back.

The lasting effects of SAH orders on sales prices and sales hazard may appear surprising at first glance. However, they are consistent with a scenario in which SAH orders temporarily increase the number of buyers waiting on the sidelines, thereby shifting the composition of active buyers toward those who are more motivated and have a higher willingness to pay. This mechanism results in pent-up demand once SAH orders are lifted, leading to persistently elevated prices and lower hazard rates, while also driving a recovery in sales and listings, as reflected in our estimated dynamic effects. We formalize this intuition by extending the baseline search model to a dynamic setting in Section 5.2.

4.3 Heterogeneity

The strong and persistent effects of SAH orders on sale hazard (inversely related to time-on-the-market) suggest that these orders do not independently impact the housing market but interact with search frictions to shape housing market dynamics. To further examine the role of search frictions, we estimate whether the effects of SAH orders are more pronounced in markets with greater search frictions, using two tract-level proxies: Internet penetration and the fraction of older housing units.

In areas with higher Internet penetration, in-person search constraints are mitigated by online photos and virtual tours, reducing reliance on physical inspections (Genesove and Han (2012); Bhuller, Ferraro, Kostøl, and Vigtel (2023)). In contrast, older homes tend to exhibit greater variability in condition and lower transparency, often requiring on-site inspections to resolve information asymmetry. Unlike newly built homes, these properties demand in-person evaluation to assess their true quality. If SAH orders impact the housing market by disrupting the search process, their effects should be stronger in markets with lower Internet access and in neighborhoods with older homes, where search frictions are more significant.

Using tract-level data from the 2019 American Community Survey, we first construct a dummy variable, *Internet below Median*, which takes a value of one if the percentage of the households with internet access in a tract is below the median value for the sample, and zero otherwise. Similarly, we define a dummy variable, *Older Neighborhood*, which takes a value of one if the fraction of housing units built before 1970 in a tract is above 70% for the sample, and zero otherwise.[16] We then interact these variables with SAH dummies and re-estimate our baseline specification with the richest set of fixed effects.

Table 4 indicates that the effects of SAH on all outcomes of interest are significantly stronger in areas with limited Internet access. This effect is particularly pronounced for sale hazard, which itself is a key indicator of search frictions. Similarly, Table 5 shows that the SAH effects are stronger and statistically significant on sales price, sales, and listings in neighborhoods with older housing stock.

[16]The results are similar using other thresholds.

Table 4: Sales Prices, Sale Hazard, Sales and Listings by the Internet Access

	(1)	(2)
	Panel A: Sales Price	Panel C: Sales
Under SAH	0.016*	-0.157***
	(0.008)	(0.033)
Under SAH x Internet below Median	0.047***	-0.076***
	(0.006)	(0.024)
After SAH	0.019***	-0.053
	(0.005)	(0.034)
After SAH x Internet below Median	0.061***	0.037***
	(0.002)	(0.037***)
Observations	511,329	3,294,487
R-squared	0.850	
	Panel B: Sale Hazard	Panel D: New Listings
Under SAH	-0.005***	-0.262***
	(0.001)	(0.029)
Under SAH x Internet below Median	-0.001**	-0.094***
	(0.000)	(0.021)
After SAH	-0.004***	-0.161***
	(0.001)	(0.031)
After SAH x Internet below Median	-0.004***	0.030***
	(0.000)	(0.007)
Observations	18,245,548	3,591,468
R-squared	0.008	
Year x Month FE	Y	Y
House characteristics	Y	N
Distance to CBD	Y	N
Infections	Y	Y
Boundary FE	Y	Y
Boundary Group FE	Y	Y
Tract FE	Y	Y

Notes: 1) The table reports results for the sample of residential properties within 1-5 miles of the county border that were sold or listed between 2017 and early 2022. 2) The dependent variables in all Panels are defined the same as in Tables 2 and 3. For property-level samples in Panels A and B, the same house characteristics and distance to the CBD as in Table 2 are included as controls. 3) Panels C and D report the estimates from the Poisson pseudo-maximum likelihood regression. 4) The infection variables include the number of new infections per capita and the percent change in new infections. 5) R-squared is not reported for the Poisson pseudo-maximum likelihood regressions because they are nonlinear so the residuals and predictions are not orthogonal. 6) ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Table 5: Sales Prices, Sale Hazard, Sales and Listings by the Fraction of Housing Units Built Before 1970

	(1)	(2)
	Panel A: Sales Price	Panel C: Sales
Under SAH	0.029***	-0.160***
	(0.008)	(0.033)
Under SAH x Older Neighborhood	0.019***	-0.083**
	(0.007)	(0.025)
After SAH	0.039***	-0.051
	(0.005)	(0.034)
After SAH x Older Neighborhood	0.017***	0.036***
	(0.002)	(0.008)
Observations	511,329	3,294,487
R-squared	0.850	
	Panel B: Sale Hazard	Panel D: New Listings
Under SAH	-0.005***	-0.263***
	(0.001)	(0.029)
Under SAH x Older Neighborhood	-0.000	-0.110***
	(0.000)	(0.022)
After SAH	-0.004***	-0.164***
	(0.001)	(0.031)
After SAH x Older Neighborhood	-0.004***	0.040***
	(0.000)	(0.007)
Observations	18,245,548	3,591,468
R-squared	0.008	
Year x Month FE	Y	Y
House characteristics	Y	N
Distance to CBD	Y	N
Infections	Y	Y
Boundary FE	Y	Y
Boundary Group FE	Y	Y
Tract FE	Y	Y

Notes: 1) The table reports results for the sample of residential properties within 1-5 miles of the county border that were sold or listed between 2017 and early 2022. 2) The dependent variables in all Panels are defined the same as in Tables 2 and 3. For property-level samples in Panels A and B, the same house characteristics and distance to the CBD as in Table 2 are included as controls. 3) Panels C and D report the estimates from the Poisson pseudo-maximum likelihood regression. 4) The infection variables include the number of new infections per capita and the percent change in new infections. 5) R-squared is not reported for the Poisson pseudo-maximum likelihood regressions because they are nonlinear so the residuals and predictions are not orthogonal. 6) ***, **, and * denote significance at the 1%, 5%, and 10% levels.

The strong and persistent SAH effects in markets with limited Internet access and older homes emphasize the need to account for search frictions. This suggests that a search-theoretic model is better suited for understanding disruptions to home search technology, which we turn to next.

5 Model

To rationalize the empirical findings, we consider a tractable search and matching model of the housing market. We begin with a version of our model with homogeneous buyers to illustrate how a disruption to search efficiency accounts for the empirical facts during SAH orders. As we show later, the mechanism through which SAH orders affect the housing market while these orders are in effect is the same regardless of whether buyers are homogeneous or heterogeneous. However, the exposition with homogeneous buyers provides a clearer intuition for the results during SAH orders.

The main ingredients of the model with homogeneous buyers are: (1) search and matching frictions in the housing market; (2) free entry of sellers in the housing market; and (3) prices are bargained. We interpret the disruption in search efficiency caused by SAH orders as a drop in search efficiency in our model. This shock is consistent with the empirical results during SAH orders and can account for the increase in prices and drop in the hazard rate, listings and sales. In addition, we show that alternative interpretations of SAH orders, such as an increase in housing demand, search costs, or entry costs, fail to account for the full range of estimated impacts. Although a combination of two shocks (for example, increased housing demand and sellers' entry costs) may rationalize the empirical facts during SAH orders, they are inconsistent with the results after SAH orders are lifted. The decline in search efficiency is the only shock that leads to a lower hazard rate for both sellers and buyers, which is crucial to account for the empirical facts post SAH orders.

In section 5.2 we study the effect of SAH orders in an environment with heterogeneous buyers in which buyers who have been unsuccessfully searching for a home become more motivated and face higher search costs. Given the drop in search efficiency from SAH orders, buyers take longer to find a house. This leads to a compositional shift in the distribution of buyers, as more buyers become motivated. Since these buyers have a higher value from matching, this compositional shift in the distribution of buyers has the same effect as a demand shock, and raises sales and listings, while still keeping prices high and the sales hazard low. This mechanism accounts for our findings post-SAH orders, since it sustains higher prices and lower sales hazard while allowing for a climb back in sales in listings.

5.1 Homogeneous Buyers and SAH Orders

Time is continuous. Agents are infinitely lived, risk-neutral, and discount future at a rate r. The housing market is subject to search frictions, which means that it takes time and costly search for sellers to sell a house and for buyers to find a home. We capture search frictions using a matching function (Pissarides, 2000) $M(v, b)$, where v is the measure of houses for sale and b the measure of buyers. The matching function satisfies the usual properties: it is increasing in each term, and displays constant returns to scale and diminishing returns. Let θ denote market tightness, i.e. $\theta = b/v$. The matching function implies that buyers find houses at a rate $m(\theta)$ and sellers find buyers at a rate $\theta m(\theta)$, with $m(\theta) \equiv M(\theta^{-1}, 1)$ decreasing in θ. Searching in the market is costly for both buyers and sellers. Buyers incur a flow cost c_B and sellers a cost c_S. When a buyer and a seller meet and a sale occurs, the price is negotiated through Nash Bargaining (Nash, 1950), where β is sellers' bargaining weight. Homeowners derive utility ε.

Households who are not homeowners search for a house to purchase (there is no entry of households/buyers). At a Poisson rate s, homeowners receive an exogenous separation shock and list their house for sale. In addition to houses listed for sale by households after a separation shock, there is also free entry of sellers through construction. Developers can build new housing at a fixed construction cost k and list it for sale. To capture depreciation, all houses are subject to a destruction shock that arrives at a Poisson rate δ.

5.1.1 Equilibrium

Let B, V, and H denote the value functions of a buyer, a house for sale, and a homeowner. They satisfy the following Bellman equations

$$rB = -c_B + m(\theta)(H - B - p), \tag{5}$$

$$rH = \varepsilon - s(H - V - B) - \delta(H - B), \tag{6}$$

$$rV = -c_S + \theta m(\theta)(p - V) - \delta V. \tag{7}$$

Prices are determined by

$$p = \arg\max_p (H - B - p)^{1-\beta}(p - V)^{\beta}.$$

Normalizing the measure of buyers to one, the law of motion for buyers is given by

$$\dot{b} = (s + \delta)h - m(\theta)b. \tag{8}$$

Intuitively, the equilibrium is determined by three conditions in three unknowns $\{p, \theta, v\}$. Free entry of sellers implies $V = k$ and gives the Housing Entry (HE) condition. Bargaining over prices gives the Price (PP) condition. The law of motion in the steady state yields the Beveridge Curve (BC). The equilibrium $\{p^*, \theta^*, b^*, v^*\}$ is unique and fully determined by these three conditions, along with $\theta = b/v$. The equilibrium conditions are given by

$$\text{HE:} \quad \frac{(r+\delta)k + c_S}{\theta m(\theta)} = p - k, \tag{9}$$

$$\text{PP:} \quad p - k = \beta \left[\frac{\varepsilon + c_B - (r+\delta)k}{r + \delta + s + (1-\beta)m(\theta)} \right], \tag{10}$$

$$\text{BC:} \quad b = \frac{s+\delta}{s + \delta + m(\theta)}. \tag{11}$$

The intuition is the following. The HE condition captures that sellers enter the market until the expected costs of having a house for sale (LHS) equal the seller's surplus from matching (RHS). The HE condition describes a downward-sloping curve in $\{\theta, p\}$ space. Higher prices increase the incentives to sell houses, so more sellers enter the market (i.e. market tightness falls). The PP condition captures that because of Nash Bargaining the price (what the seller gets from matching) equals the entry cost k plus a share β of the total surplus from matching. The total surplus is increasing in market tightness, so PP is an increasing relationship between p and θ, since a higher θ lowers the effective discount rate $r + \delta + s + (1-\beta)m(\theta)$ and raises the surplus from matching. The BC captures the usual mechanism in Diamond-Mortensen-Pissarides (DMP) models. As more houses are listed for sale, and tightness decreases, it becomes easier for buyers to find houses, so the measure of buyers falls.

5.1.2 The Effect of Stay-at-Home (SAH) Orders

This section applies the model above to examine the effects of stay-at-home (SAH) orders. Assume the matching function is Cobb-Douglas, and let $m(\theta) = \mu\theta^{-\eta}$, where μ captures search efficiency. As a result, $\theta m(\theta) = \mu\theta^{1-\eta}$. We interpret SAH as a decline in search efficiency μ, which leads to fewer matches despite the same number of buyers and sellers in the market. With significantly reduced foot traffic and the inability to conduct in-person home visits, a drop in μ serves as a natural proxy for SAH. We demonstrate that the comparative statics derived from a decline in search efficiency align closely with the estimated housing market responses during and after SAH, as reported earlier in Section 4. Later in this section, we also explore alternative interpretations of SAH, such as increased search costs or heightened demand, and demonstrate that neither of these align with our empirical findings.[17]

Figure 6 depicts the effect of a drop in the search efficiency μ on the steady-state equilibrium outcomes. A drop in search efficiency leads to a shift of the HE to the right. Intuitively, holding market tightness constant, a drop in search efficiency raises expected costs, so to ensure entry sellers must be compensated with higher prices. At the same time, the drop in μ shifts the PP curve upwards. Holding market tightness constant, a drop in μ lowers the effective discount rate, so the overall match surplus increases. Because of bargaining, this raises prices. Finally, the drop in μ also shifts the BC, through the usual mechanism in DMP models.

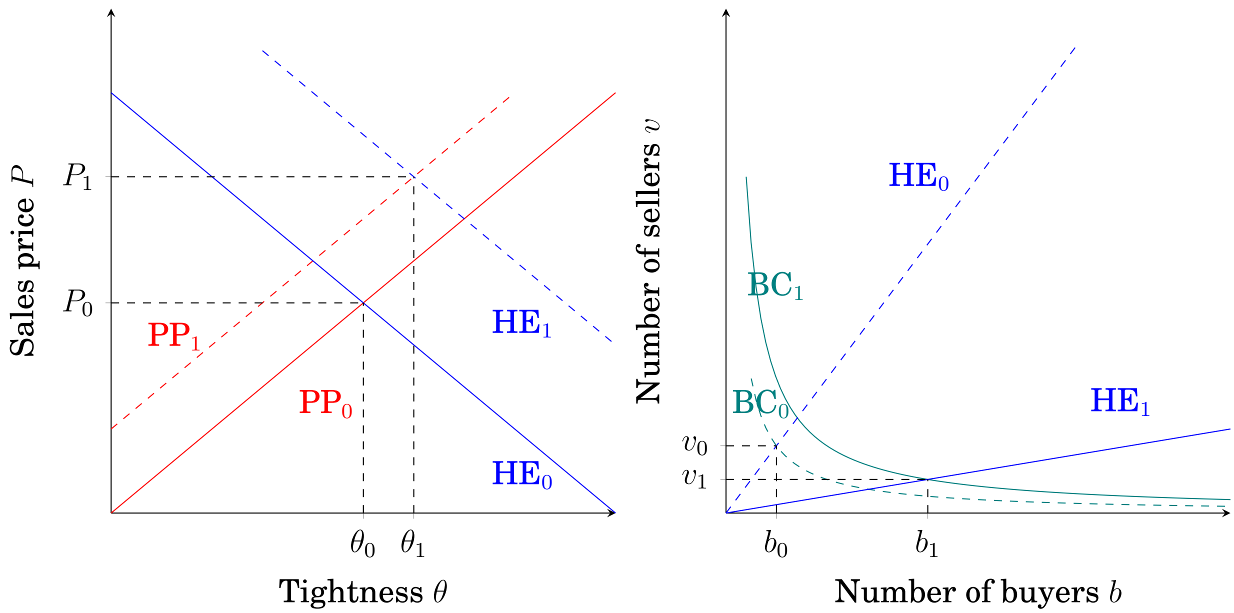
As shown in the left panel of Figure 6, upward shifts in the HE and PP curves lead to a clear increase in sales prices. With a sufficient drop in search efficiency μ, the HE shifts more to the right than the BC, as illustrated in the right panel. This results in a disproportionate increase in buyers, a decline in vacancies, and a rise in market tightness θ, which also indicates that HE shifts upward more than PP, as shown in the left panel.

The decline in search efficiency μ outweighs the rise in market tightness θ, causing a reduction in the sale hazard $\mu m(\theta)$. The effect on houses for sale and new listings is ambiguous because buyers and market tightness move in opposite directions. However, both tend to decrease when market tightness is high, which occurs under a significant drop in search efficiency. The Appendix A provides detailed proofs of these comparative statics results.

In summary, a significant decline in search efficiency results in higher prices,

[17]Although a combination of shocks may be able to rationalize the emprical facts during SAH, they all lead to an increase in the hazard rate for buyers since market tightness increases. Therefore, a combination of shocks is unable to account for the empirical facts after SAH are lifted, as we show later.

Figure 6: The Effect of a Drop in search efficiency μ

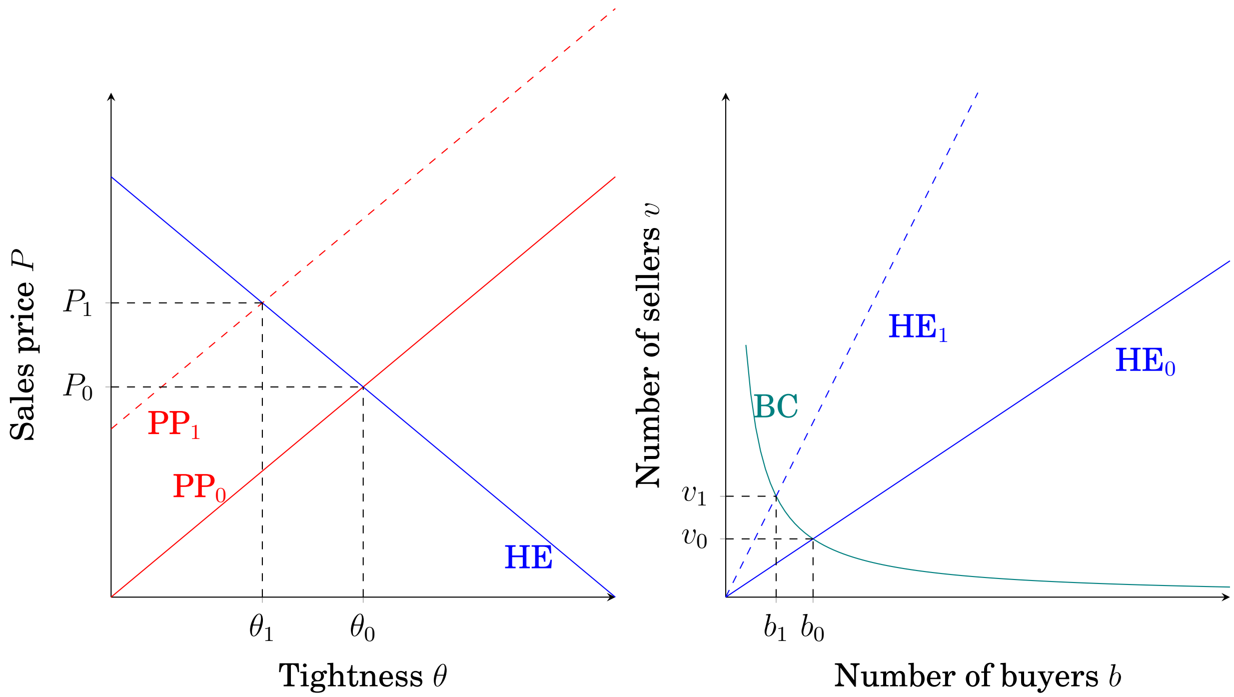


lower sale hazard, and decreases in both sales and new listings. These predictions are fully consistent with our empirical findings for the under-SAH period. Through the lens of the model, these effects arise because reduced search efficiency discourages sellers from entering the market, while those who do enter demand higher prices. Meanwhile, a long queue of buyers forms, yet the total number of transactions declines due to the sharp drop in search efficiency.

5.1.3 Alternative Interpretations of SAH Orders

Our empirical findings that the effects of SAH are more pronounced in markets with greater search frictions provide strong empirical support for our view that SAH represents a shock to search efficiency. Nevertheless, one might question whether a decline in search efficiency is the only interpretation for SAH. For instance, SAH could be viewed as as a proxy for a positive demand shock to ε or an increase in buyers' search costs c_B. A demand shock may reflect higher demand for living space at home, while increased search costs arise from reduced foot traffic, making in-person visits and inspections costly – both plausible scenarios under SAH.

Figure 7: The Effect of a Demand Shock ε or an Increase in Buyer's Search Costs c_B



To evaluate these alternative interpretations, we derive comparative statics for ε and c_B. Both shocks similarly affect the price-setting (PP) curve, as shown in Figure 7. In the surplus-sharing rule, ε directly contributes to buyers' surplus, influencing prices through bargaining. Similarly, search costs c_B enter the surplus-sharing rule because buyers avoid these costs upon matching. Under either shock, the PP shifts upward, while the housing equilibrium (HE) remains unchanged, leading to a decline in market tightness θ.

In the $\{b, v\}$ space the HE curve rotates left due to lower market tightness, while the BC remains unchanged. Consequently, an increase in ε or c_B leads to higher prices, a reduction in sale hazard, fewer buyers, and increases in both sales and new listings. These predicted increases in sales and new listings, however, are the opposite of what we empirically find, strongly supporting the interpretation of SAH as a decline in search efficiency. In addition, the drop in sellers' hazard rate is not accompanied by a similar drop in buyer's hazard rate, since the lower seller's hazard rate is driven by a drop in market tightness θ. With a constant search efficiency μ, a lower market tightness implies that the hazard rate for buyers $m(\theta)$ increases. Therefore, buyers find houses more quickly during SAH orders, and so the model cannot generate the compositional shifts required to account for the post SAH orders facts.

Finally, one may also interpret SAH orders as increasing costs for sellers, either through an increase in k or c^S. These supply shocks shift both the PP and HE curves upward, since higher costs require higher prices for sellers to enter, and push prices higher due to bargaining. It is straightforward to prove that the shift in the HE curve dominates, so that overall prices, market tightness and the sales hazard increase, while listings and sales both decrease. These results are inconsistent with the observed drop in the hazard rate during SAH orders.

One may argue that the right combination of a demand and a supply shock may explain the observed behavior of the housing market during SAH orders. However, this combination of supply and demand shocks is inconsistent with the observed patterns after SAH orders. Just as with a demand shock, a combination of supply and demand shocks raises market tightness. With a constant search efficiency μ, the hazard rate for buyers increases, which leads to the opposite compositional effect required to match empirical facts after SAH orders are lifted. A shock to search efficiency is the only shock that leads to a lower hazard rate for both buyers and sellers.

5.2 Motivated Buyers and Post-SAH Orders

So far, we have shown that the estimated under-SAH effects on the housing market align with a search-theoretic model experiencing a negative shock to search efficiency. The remaining question is whether this model can also explain the post-SAH effects. Our empirical estimates indicate that after SAH orders are lifted, prices continue to increase and hazard rates remain low, but both sales and listings climb back, with even some overshooting in some cases. Our model with homogeneous buyers predicts that once SAH orders are lifted, there should be a return of all variables to their original value pre SAH orders. Therefore, the challenge becomes finding a mechanism that continues to raise prices and lower the hazard rate once SAH orders are lifted, while allowing for an increase in sales and listings.

One mechanism through which SAH orders can create these persistent effects is a shift in the composition of buyers towards buyers who value housing more while a SAH order is in place. Such a compositional shift in the distribution of buyers has the same effect on the housing market as a demand shock depicted in Figure 7, and increases prices, sales and listings while reducing hazard rates. If this compositional effect happens progressively and is persistent, SAH orders have persistent effects beyond the duration of the SAH policy. In this section, we extend the baseline framework by introducing heterogeneity among buyers to illustrate such a mechanism through which the SAH orders can explain the post-SAH boom.

We propose an environment that features heterogeneity in the spirit of Albrecht et al. (2007) with motivated and relaxed buyers. All buyers start as relaxed buyers, but the longer they search for a house, the more likely they are to become motivated. Motivated buyers are assumed to have higher search costs. Therefore, they derive a higher value from matching. Although we assume that buyers' heterogeneity comes from search costs, the results are equivalent to assuming that relaxed and motivated buyers have utilities ε^H and ε^L respectively, with $\varepsilon^H > \varepsilon^L$. In the environment, when the matching rate for buyers $m(\theta)$ drops during SAH, more buyers become motivated. Because the distribution of buyers takes time to adjust, sellers face a compositional change in the distribution of buyers towards those who value housing more. This mechanism acts in the same way as a demand shock as captured in Figure 7, but arises endogenously in the environment as a result of SAH orders.

Consider our baseline environment from the previous section, except that there are now two types of buyers: <u>motivated</u> and <u>relaxed</u> buyers. All buyers start searching as relaxed buyers with search costs c_B^L. At a rate λ relaxed buyers become desperate and their search costs increase to $c_B^H > c_B^L$. Let ϕ denote the endogenous fraction of desperate buyers, i.e. $\phi = b^H/(b^H + b^L)$, where b^H and b^L are the number of desperate and relaxed buyers. The notation remains the same as in the baseline model, except that H and L denote motivated and relaxed variables respectively.

5.2.1 Equilibrium

Let B^L and B^H denote the value functions for relaxed and motivated buyers. The Bellman equations for households are given by

$$rB^L = -c_B^L + m(\theta)(H - B^L - p^L) + \lambda(B^H - B^L), \tag{12}$$

$$rB^H = -c_B^H + m(\theta)(H - B^H - p^H), \tag{13}$$

$$rH = \varepsilon - s(H - V - B^L) - \delta(H - B^L), \tag{14}$$

where p^L and p^H denote the price paid by relaxed and motivated buyers:

$$p^H = V + \beta(H - B^H - V),$$

$$p^L = V + \beta(H - B^L - V).$$

The intuition is the same as in the baseline model with homogeneous buyers, except that the above equations capture that relaxed buyers become desperate at a rate λ. Desperate or motivated buyers will be willing to pay a different – higher – price as we show shortly. It is because the surplus from matching is higher, which leads to a higher price due to bargaining.

The Bellman equation for sellers is given by

$$rV = -c_S + \theta m(\theta)[\phi(p^H - V) + (1 - \phi)(p^L - V)] - \delta V. \tag{15}$$

Relative to the model with homogeneous buyers, sellers now face an endogenous distribution of heterogeneous buyers. A fraction ϕ of buyers are motivated and pay the price p^H, whereas a fraction $1-\phi$ are desperate and pay the price p^L. An additional equilibrium outcome in the model with heterogeneity is the endogenous distribution of buyers ϕ.

Let h denote the measure of homeowners. Normalize the size of the population to one, so that $b^L + b^H + h = 1$. The dynamics of the number of homeowners, buyers, and sellers are given by

$$\dot{h} = m(\theta)(1-h) - (s+\delta)h,$$

$$\dot{b}^L = (s+\delta)h - m(\theta)b^L - \lambda b^L,$$

$$\dot{b}^H = \lambda b^L - m(\theta)b^H.$$

The above equations capture that buyers leave the pool of relaxed buyers either because they find a house or because they become motivated at a rate λ. The flow into the stock of relaxed buyers comes from separations. Relaxed buyers become motivated at a rate λ and buyers leave the pool of motivated buyers when they find a house. The intuition for the flow equation for homeowners h is the same as in the model with homogeneous buyers.

In steady state, $\dot{b}^L = \dot{b}^H = \dot{h} = 0$, so the above flow equations give the following equilibrium measures of buyers and sellers

$$h = \frac{m(\theta)}{m(\theta)+s+\delta}, \tag{16}$$

$$b^L = \frac{s+\delta}{m(\theta)+s+\delta}\frac{m(\theta)}{m(\theta)+\lambda}, \tag{17}$$

$$b^H = \frac{s+\delta}{m(\theta)+s+\delta}\frac{\lambda}{m(\theta)+\lambda}. \tag{18}$$

Using the last two equations gives the Beveridge Curve (BC)

$$b = b^L + b^H = \frac{s+\delta}{s+\delta+m(\theta)}, \tag{19}$$

which is the same as in the homogeneous buyers model. The fraction of motivated buyers, ϕ, is then given by

$$\phi \equiv \frac{b^H}{b^H + b^L} = \frac{\lambda}{\lambda + m(\theta)}. \tag{20}$$

A decrease in the matching rate $m(\theta)$ increases the fraction of motivated buyers, since buyers find houses less quickly and, therefore, more of them become motivated. As a result, the fraction ϕ of motivated buyers rises.

The equilibrium is derived in a similar way as in the model with homogeneous buyers. Free entry condition implies that $V = k$. Then the free entry condition can be substituted into to the Bellman equation for sellers to get the Housing Entry (HE) condition

$$\bar{p} - k = \frac{c_S + (r+\delta)k}{\theta m(\theta)}, \tag{21}$$

where $\bar{p} = \phi p^H + (1-\phi)p^L$ denotes the average price.

To solve for the prices p^H and p^L, first use the Bellman equations for motivated and relaxed buyers, which imply

$$B^H - B^L = -\frac{c_B^H - c_B^L}{r + \lambda + (1-\beta)m(\theta)} < 0.$$

The above shows that $B^H < B^L$, as expected, given that motivated buyers face a large search cost. Let $S_H = H - B^H - k$ and $S_L = H - B^L - k$ denote the match surplus with a motivated and relaxed buyer respectively. Using the Bellman equations and free entry gives

$$S^L = \frac{\varepsilon + c_B^L - (r+\delta)k + \frac{\lambda}{r+(1-\beta)m(\theta)+\lambda}(c_B^H - c_B^L)}{r+s+\delta+(1-\beta)m(\theta)},$$
$$S^H = \frac{\varepsilon + c_B^H - (r+\delta)k + \frac{s+\delta}{r+(1-\beta)m(\theta)+\lambda}(c_B^H - c_B^L)}{r+s+\delta+(1-\beta)m(\theta)}.$$

Because $S^H - S^L = -(B^H - B^L)$, $S^H > S^L$, i.e. matches with motivated buyers lead to higher prices. Using the above and Nash Bargaining gives prices

$$p^L - k = \beta \left[\frac{\varepsilon + c_B^L - (r+\delta)k + \frac{\lambda}{r+(1-\beta)m(\theta)+\lambda}(c_B^H - c_B^L)}{r+s+\delta+(1-\beta)m(\theta)} \right], \tag{22}$$
$$p^H - k = \beta \left[\frac{\varepsilon + c_B^H - (r+\delta)k + \frac{s+\delta}{r+(1-\beta)m(\theta)+\lambda}(c_B^H - c_B^L)}{r+s+\delta+(1-\beta)m(\theta)} \right], \tag{23}$$

and the price-setting (PP) curve using expressions for p^H and p^L from the above:

$$\bar{p} = \phi p^H + (1-\phi)p^L. \tag{24}$$

The equilibrium is a tuple $\{p^{H*}, p^{L*}, \theta^*, \phi^*, b^*, v^*\}$ that satisfies the Housing Entry HE condition (21), the price equations (23) and (22), the Beveridge Curve (19), the distribution (20) and $\theta = b/v$. As with the model with homogeneous buyers, it is easy to verify that the equilibrium exists and is unique.

5.2.2 Comparative Statics during SAH Orders

We now analyze the effect of a drop in search efficiency, μ, brought about by SAH orders. Our main conclusion is that during SAH orders the model with heterogeneity mimics the model with homogeneous buyers, and that SAH lead to higher prices, and lower hazard rates, sales and listings during SAH orders. For analytical tractability, we assume that the decrease in the search efficiency during SAH orders affects all the market outcomes immediately with the exception of the distribution of buyers. In our model, this distribution evolves slowly as an increasing number of relaxed buyers become motivated. Rather than modelling this gradual adjustment through the SAH period, we assume that the distribution adjusts in one step at the end of the SAH orders. This simplification allows us to isolate the effect of lower search efficiency during the SAH period to simplify the exposition. Once SAH orders are lifted, we update the fraction of motivated buyers to reflect the reduced search efficiency and then examine the subsequent post-SAH effects.

In this section, we show that the predictions of the extended model with heterogeneous buyers are the same as in the model with homogeneous buyers from Section 5.1.2. The following section will address the impact of the adjustment in the buyers distribution and the reversal of SAH orders. We proceed by deriving the equilibrium equation determining the tightness θ. Then we show that a drop in the search efficiency reduces the sale hazard $\theta m(\theta)$, increases the number of buyers and prices, reduces sales, and has an ambiguous effect on the number of listings, just as in the model with homogeneous buyers.

To get the equilibrium condition on the market tightness, use the price equations (22) and (23) to find

$$p^H - p^L = \beta \frac{c_B^H - c_B^L}{r + \lambda + (1-\beta)m(\theta)}. \tag{25}$$

Then define $\psi(m(\theta), \phi)$ as

$$\psi(m(\theta), \phi) \equiv \frac{\lambda + \phi(r + s + \delta + (1-\beta)m(\theta))}{r + \lambda + (1-\beta)m(\theta)}. \tag{26}$$

Combining (25) and the price equations (22) and (23) with the housing entry condition (21) gives

$$\beta[\varepsilon + c_B^L - (r+\delta)k + \psi(m(\theta), \phi)] = \frac{c_S + (r+\delta)k}{\theta m(\theta)}(r + s + \delta + (1-\beta)m(\theta)]. \tag{27}$$

The assumption that the distribution ϕ takes time to adjust and remains unchanged during the SAH is equivalent to assuming that $\partial\psi(m(\theta),\phi)/\partial\phi = 0$ during the SAH orders. Define Δ as

$$\Delta = -\frac{\partial\psi(m(\theta),\phi)}{\partial m(\theta)}\frac{m(\theta)}{\psi(m(\theta),\phi)}\frac{\psi(m(\theta),\phi)(c_B^H - c_B^L)}{\varepsilon + c_B^L - (r+\delta)k + \psi(m(\theta),\phi)(c_B^H - c_B^L)}. \tag{28}$$

Log-differentiating $\psi(m(\theta),\phi)$ gives that

$$\frac{\partial\psi(m(\theta),\phi)}{\partial m(\theta)}\frac{m(\theta)}{\psi(m(\theta),\phi)} = -\frac{(1-\beta)m(\theta)[\lambda(1-\phi)+\phi(s+\delta)]}{[\lambda+\phi(r+s+\delta+(1-\beta)m(\theta)][r+\lambda+(1-\beta)m(\theta)]}. \tag{29}$$

Using the above result it is straightforward that $\Delta \in (0,1)$.

Log-differentiating (27) with respect to μ gives the elasticity $\varepsilon_{\theta,\mu}$ of market tightness with respect to μ

$$\varepsilon_{\theta,\mu} = \frac{(1-\beta)m(\theta)\Delta - (r+s+\delta)(1-\Delta)}{(r+s+\delta)(1-\eta(1-\Delta)) + (1-\beta)m(\theta)(1+\eta\Delta)}. \tag{30}$$

Note that with $\Delta = 0$ the above elasticity equals the elasticity in the baseline model with homogeneous buyers.

To derive the effect of a drop in μ on the sale hazard, use that

$$\frac{d(\theta m(\theta))}{d\mu}\frac{\mu}{\theta m(\theta)} = 1 + (1-\eta)\varepsilon_{\theta,\mu}. \tag{31}$$

Combining the above result with (30) gives

$$\frac{d(\theta m(\theta))}{d\mu}\frac{\mu}{\theta m(\theta)} = \frac{(r+s+\delta)\Delta + (1-\beta)m(\theta)(1+\Delta)}{(r+s+\delta)(1-\eta(1-\Delta)) + (1-\beta)m(\theta)(1+\eta\Delta)}. \tag{32}$$

Finally, we can access the effect of the search efficiency on the sales hazard. As in the baseline, the above is positive and, therefore, a drop in search efficiency μ leads to a lower sale hazard.

Following a similar procedure as for the sale hazard, the elasticity of buyers $b = (s+\delta)/(s+\delta+m(\theta))$ with respect to search efficiency μ is given by

$$\frac{db}{d\mu}\frac{\mu}{b} = -\frac{m(\theta)}{s+\delta+m(\theta)}(1-\eta\varepsilon_{\theta,\mu}). \tag{33}$$

Substituting $\varepsilon_{\theta,\mu}$ from above gives

$$1-\eta\varepsilon_{\theta,\mu} = \frac{(r+s+\delta)+(1-\beta)m(\theta)}{(r+s+\delta)(1-\eta(1-\Delta))+(1-\beta)m(\theta)(1+\eta\Delta)} > 0. \tag{34}$$

Therefore, the measure of buyers increases as search efficiency drops, as in the model with homogeneous buyers.

The above expression is also the elasticity of $m(\theta)$ with respect to the search efficiency:

$$\frac{dm(\theta)}{d\mu} = 1-\eta\varepsilon_{\theta,\mu} > 0. \tag{35}$$

Thus, a decrease in the search efficiency μ leads to lower $m(\theta)$ and higher prices from (23) and (22).

For sales, log-differentiating with respect to μ gives

$$\frac{d\text{Sales}}{d\mu}\frac{\mu}{\text{Sales}} = \left(\frac{s+\delta}{s+\delta+m(\theta)}\right)(1-\eta\varepsilon_{\theta,\mu}) > 0. \tag{36}$$

Therefore, sales decrease with the drop in search efficiency μ. As in the homogeneous buyers environment, the sign of the effect on vacancies is ambiguous and is negative under certain parameter conditions. Thus, the effects of lower search efficiency in the model with heterogeneous buyers are the same as in the model with homogeneous buyers: prices increase, while the hazard rate, sales and inventory all decrease.

5.2.3 Comparative Statics after SAH Orders

Once SAH orders are lifted, search efficiency returns to its original pre-SAH order. However, the distribution of buyers post-SAH differs because it adjusted in response to the shock to search efficiency experienced during the SAH orders. During the SAH orders fewer buyers were able to purchase homes due to lower matching rate. Thus, more of them became desperate by the time the SAH orders were lifted. Absent this compositional effect, we would observe a gradual return of all variables to their original pre-SAH values after search efficiency is restored to its original value, i.e. there would be a drop in prices and an increase in hazard, sales and listings all the way back to their values prior to SAH orders. This would be inconsistent with our empirical findings that after SAH orders are lifted prices continue to increase and the hazard rate remains persistently low, while sales and listings climb back to their initial value, with some overshooting in some cases. Our mechanism with heterogeneity allows us to keep prices high and hazard low post-SAH orders, while allowing a climb back in sales and listings.

Formally, the search efficiency μ returns to its original value, and the fraction of motivated buyers ϕ now adjusts in response to the drop in μ during the SAH orders. The effect of a decrease in μ on $m(\theta)$ is given by

$$\frac{dm(\theta)}{d\mu} = 1 - \eta\varepsilon_{\theta,\mu} > 0, \tag{37}$$

which is positive from (34). Therefore, as μ decreases the rate $m(\theta)$ decreases, which raises the fraction of motivated buyers $\phi = \lambda/(\lambda + m(\theta))$ from (20). Intuitively, with lower search efficiency buyers take longer to find a house, which raises the risk of becoming desperate. As a result, buyers become desperate at a higher rate and the distribution of buyers features more desperate buyers.

The effects of the increased share of motivated buyers are the same as a positive demand shock in the baseline model with homogeneous buyers because $p^H > p^L$ and a larger share of motivated buyers ϕ moves the price-setting (PP) curve given by equations (23), (22), (24) to the left as in Figure 7. Consequently, during the post-SAH period, we continue to observe higher prices and a reduced sales hazard driven by this compositional effect. Meanwhile, the corresponding increase in sales and new listings indicates that the reductions caused by SAH are gradually reversing. Some of this reversal is due to the return of search efficiency to its original level, but also due to the compositional effect that raises sales and listings. As this recovery takes time, the post-SAH period shows fewer negative effects than the under-SAH period when compared to pre-pandemic levels. In fact, our model does allows for some overshooting of sales and listings, as we observe in our empirical estimates in some cases (for example for houses with internet speed below median) if the compositional effect is strong enough. Overall, our results are fully consistent with the dynamic responses revealed by our earlier estimates.

This compositional effect requires the hazard rate for buyers to drop in response to SAH orders. A shock to search efficiency is the only shock that leads to a drop in both sellers' and buyers' hazard rates, so it is the only shock consistent with our empirical results both during and after SAH orders. A combination of demand and supply shocks lead to a drop in the hazard rate for sellers, but also to a corresponding increase in buyers' hazard rate (absent a shock to search efficiency). Therefore, this combination of demand and supply shocks is unable to match our estimates after SAH orders are lifted.

5.3 Welfare

The welfare implications depend on the whether we are considering an environment with homogeneous or heterogeneous buyers. In our baseline environment, the only externalities are the usual congestion/thick market externalities present in DMP models. Sellers do not internalize that as they post more vacancies they create congestion for other sellers and make it harder for them to sell their home. At the same time, they do not internalize that by posting more vacancies they make it easier for buyers to find homes. Both externalities cancel out when the Hosios-Mortensen-Pissarides (HMP) condition holds and $\eta = \beta$, in which case the decentralized economy is efficient. The effect of SAH orders on welfare thus depends on whether the HMP condition holds. Since a drop in search efficiency raises market tightness, the drop in search efficiency induced by SAH orders improves welfare if and only if market tightness is inefficiently low in the pre-SAH decentralized allocation, i.e. in markets with low number of buyers relative to available houses for sale. In that case, the SAH orders raise market tightness and bring the economy closer to the efficient allocation. However, in markets with inefficiently high number of buyers relative to offered houses for sale, conditions that are usually associated with markets with affordability issues, a SAH order may worsen affordability issues by further raising market tightness above the efficient level. It is worth noting that this welfare analysis omits the potential negative externalities due to the spread of COVID-19. As buyers visit more houses, the risk of spreading COVID-19 increases, a cost that buyers and sellers do not internalize (Kapička and Rupert, 2022; Jackson and Ortego-Marti, 2024)

The same is not true in an environment with heterogeneity because there is an additional externality. Sellers do not internalize that if they post more houses for sale they reduce the risk that buyers become motivated, which is costly from a social planner's point of view. With this compositional externality, the decentralized allocation is inefficient even if the HMP condition holds.[18] Intuitively, the HMP condition eliminates the congestion/thick market externality, but the social planner needs an additional tool to regulate the entry of sellers and internalize the compositional externality. Because SAH orders lowers the finding rate for buyers, SAH orders worsen

[18]This result is similar to Gabrovski and Ortego-Marti (In press).

this compositional externality, even in cases where they alleviate the congestion externality. SAH orders may, therefore, have unintended consequences for affordability and welfare.

6 Conclusion

Using detailed micro-level housing data and a quasi-natural experiment based on the staggered adoption of stay-at-home (SAH) orders, we provide causal evidence that disruptions to home search significantly increased housing prices while reducing sales hazard, transaction volumes, and new listings. These effects were more pronounced in markets with greater search frictions, such as older neighborhoods and areas with lower internet penetration. While sales and listings rebounded quickly after SAH orders were lifted, prices remained elevated, and sales hazard stayed persistently low.

To explain these findings, we develop a search-and-matching model with heterogeneous buyers, in which buyers who have been searching for longer periods of time become more desperate and value owning a house more. In our environment SAH orders represent an exogenous decline in search efficiency, which is well supported empirically by our findings that the effects of SAH are stronger in markets with more prevalent search frictions. This framework accounts for the observed price increases alongside a slowdown in sales and listings, as traditional search activities were interrupted during SAH orders. Since buyers find houses at a lower rate due to SAH orders, more buyers become motivated. After SAH orders are lifted, this compositional shift of buyers towards motivated buyers has the same effects as a demand shock, and lifts prices, sales and listings, while keeping the hazard rates low. This additional compositional mechanism explains why prices remain high and hazard rate low after SAH orders are lifted, while allowing for a climb back of sales and listings. Alternative explanations — such as shifts in housing demand and/or higher supply costs — fail to fully capture the empirical patterns we document. In particular, our model highlights how SAH orders not only disrupt search efficiency during the restriction period but also induce a compositional shift in the buyer pool, leading to prolonged market imbalances.

More broadly, our findings underscore the importance of incorporating search frictions when evaluating the unintended economic consequences of public health policies. Policies aimed at curbing COVID-19 infections, such as stay-at-home orders, inadvertently altered housing market dynamics by affecting the search technology. These disruptions created lasting effects, sustaining elevated housing prices even after SAH orders were lifted.

References

ACHARYA, V. V., R. ENGLE, M. JAGER, AND S. STEFFEN (2024): "Why did bank stocks crash during COVID-19?" The Review of Financial Studies, 37, 2627–2684.

ALBRECHT, J., A. ANDERSON, E. SMITH, AND S. VROMAN (2007): "Opportunistic matching in the housing market," International Economic Review, 48, 641–664.

ALBRECHT, J., P. A. GAUTIER, AND S. VROMAN (2016): "Directed search in the housing market," Review of Economic Dynamics, 19, 218–231.

ANENBERG, E. AND D. RINGO (2024): "Volatility in Home Sales and Prices: Supply or Demand?" Journal of Urban Economics, 139, 103610.

AREFEVA, A. (2017): "Housing Markets: Auctions, Microstructure Noise, and Weekly Patterns," Mimeo, University of Wisconsin-Madison.

ARNOTT, R. (1989): "Housing vacancies, thin markets, and idiosyncratic tastes," The Journal of Real Estate Finance and Economics, 2, 5–30.

AUGUSTIN, P., V. SOKOLOVSKI, M. G. SUBRAHMANYAM, AND D. TOMIO (2022): "In sickness and in debt: The COVID-19 impact on sovereign credit risk," Journal of Financial Economics, 143, 1251–1274.

BADARINZA, C., V. BALASUBRAMANIAM, AND T. RAMADORAI (2024): "In Search of the Matching Function in the Housing Market," Available at SSRN.

BAEK, C., P. B. MCCRORY, T. MESSER, AND P. MUI (2021): "Unemployment effects of stay-at-home orders: Evidence from high-frequency claims data," Review of Economics and Statistics, 103, 979–993.

BHULLER, M., D. FERRARO, A. R. KOSTØL, AND T. C. VIGTEL (2023): "The internet, search frictions and aggregate unemployment," Tech. rep., National Bureau of Economic Research.

BOYARCHENKO, N., A. KOVNER, AND O. SHACHAR (2022): "It's what you say and what you buy: A holistic evaluation of the corporate credit facilities," Journal of Financial Economics, 144, 695–731.

BURNSIDE, C., M. EICHENBAUM, AND S. REBELO (2016): "Understanding booms and busts in housing markets," Journal of Political Economy, 124, 1088–1147.

CHEN, J. AND J. ROTH (2023): "Logs with Zeros? Some Problems and Solutions*," The Quarterly Journal of Economics, qjad054.

COHN, J. B., Z. LIU, AND M. I. WARDLAW (2022): "Count (and count-like) data in finance," Journal of Financial Economics, 146, 529–551.

COIBION, O., Y. GORODNICHENKO, AND M. WEBER (2020): "The cost of the covid-19 crisis: Lockdowns, macroeconomic expectations, and consumer spending," Tech. rep., National Bureau of Economic Research.

DIAZ, A. AND B. JEREZ (2013): "House Prices, Sales, And Time On The Market: A Search-Theoretic Framework," International Economic Review, 54, 837–872.

D'LIMA, W., L. A. LOPEZ, AND A. PRADHAN (2022): "COVID-19 and housing market effects: Evidence from U.S. shutdown orders," Real Estate Economics, 50, 303–339.

FAHLENBRACH, R., K. RAGETH, AND R. M. STULZ (2021): "How valuable is financial flexibility when revenue stops? Evidence from the COVID-19 crisis," The Review of Financial Studies, 34, 5474–5521.

GABROVSKI, M. AND V. ORTEGO-MARTI (2019): "The cyclical behavior of the Beveridge Curve in the housing market," Journal of Economic Theory, 181, 361–381.

——— (2021): "Search and credit frictions in the housing market," European Economic Review, 134, 103699.

——— (2025): "Home construction financing and search frictions in the housing market," Review of Economic Dynamics, 55, 101253.

——— (In press): "A note on efficiency in the housing market with search frictions," Macroeconomic Dynamics.

GAMBER, W., J. GRAHAM, AND A. YADAV (2023): "Stuck at home: Housing demand during the COVID-19 pandemic," Journal of Housing Economics, 59, 101908, cOVID-19's Impacts on Housing Markets.

GARRIGA, C. AND A. HEDLUND (2020): "Mortgage Debt, Consumption, and Illiquid Housing Markets in the Great Recession," American Economic Review, 110, 1603–34.

GENESOVE, D. AND L. HAN (2012): "Search and matching in the housing market," Journal of Urban Economics, 72, 31–45.

GERARDI, K., P. S. WILLEN, AND D. H. ZHANG (2023): “Mortgage prepayment, race, and monetary policy,” Journal of Financial Economics, 147, 498–524.

GOLDSTEIN, I., R. S. KOIJEN, AND H. M. MUELLER (2021): “COVID-19 and its impact on financial markets and the real economy,” The Review of Financial Studies, 34, 5135–5148.

GOOLSBEE, A. AND C. SYVERSON (2021): “Fear, lockdown, and diversion: Comparing drivers of pandemic economic decline 2020,” Journal of public economics, 193, 104311.

GUPTA, A., V. MITTAL, J. PEETERS, AND S. VAN NIEUWERBURGH (2022): “Flattening the curve: Pandemic-Induced revaluation of urban real estate,” Journal of Financial Economics, 146, 594–636.

GUREN, A. M. (2018): “House price momentum and strategic complementarity,” Journal of Political Economy, 126, 1172–1218.

HADDAD, V., A. MOREIRA, AND T. MUIR (2021): “When selling becomes viral: Disruptions in debt markets in the COVID-19 crisis and the Fed’s response,” The Review of Financial Studies, 34, 5309–5351.

HAN, L., J. HATFIELD, AND S.-H. HONG (2023): “Voting with Your Mortgage: The Value of Democratic Governance,” Working Paper.

HAN, L. AND S.-H. HONG (2024): “Cash is King? Evidence from Housing Markets,” Review of Finance, 28, 2083–2188.

HAN, L., C. LUTZ, B. SAND, AND D. STACEY (2021): “The Effects of a Targeted Financial Constraint on the Housing Market,” Review of Financial Studies, 34, 3741–3788.

HAN, L., L. R. NGAI, AND K. D. SHEEDY (2025): "To Own Or to Rent?: The Effects of Transaction Taxes on Housing Markets," Review of Economic Studies.

HAN, L. AND W. C. STRANGE (2015): "The microstructure of housing markets: Search, bargaining, and brokerage," Handbook of regional and urban economics, 5, 813–886.

HEAD, A., H. LLOYD-ELLIS, AND H. SUN (2014): "Search, liquidity, and the dynamics of house prices and construction," American Economic Review, 104, 1172–1210.

——— (2016): "Search, liquidity, and the dynamics of house prices and construction: Corrigendum," American Economic Review, 106, 1214–1219.

JACKSON, P. AND V. ORTEGO-MARTI (2024): "Skill loss during unemployment and the scarring effects of the COVID-19 pandemic," Labour Economics, 102516.

KAPIČKA, M. AND P. RUPERT (2022): "Labor markets during pandemics," Journal of Economic Theory, 204, 105520.

KARGAR, M., B. LESTER, D. LINDSAY, S. LIU, P.-O. WEILL, AND D. ZÚÑIGA (2021): "Corporate bond liquidity during the COVID-19 crisis," The Review of Financial Studies, 34, 5352–5401.

KIM, D., D. RAIHA, Y. SEO, AND J. FREYBOTE (2023): "Urban flight: A short-term phenomenon or long-term trend?" Real Estate Economics, 51, 1356–1375.

KOTOVA, N. AND A. L. ZHANG (2020): "Search frictions and idiosyncratic price dispersion in the us housing market," Available at SSRN 3386353.

LEVINE, R., C. LIN, M. TAI, AND W. XIE (2021): "How did depositors respond to COVID-19?" The Review of Financial Studies, 34, 5438–5473.

LI, L., Y. LI, M. MACCHIAVELLI, AND X. ZHOU (2021): "Liquidity restrictions, runs, and central bank interventions: Evidence from money market funds," The Review of Financial Studies, 34, 5402–5437.

LING, D. C., C. WANG, AND T. ZHOU (2020): "A first look at the impact of COVID-19 on commercial real estate prices: Asset-level evidence," The Review of Asset Pricing Studies, 10, 669–704.

LIU, S. AND Y. SU (2021): "The impact of the COVID-19 pandemic on the demand for density: Evidence from the U.S. housing market," Economics Letters, 207, 110010.

MA, Y., K. XIAO, AND Y. ZENG (2022): "Mutual fund liquidity transformation and reverse flight to liquidity," The Review of Financial Studies, 35, 4674–4711.

MOEN, E. R., P. T. NENOV, AND F. SNIEKERS (2021): "Buying first or selling first in housing markets," Journal of the European Economic Association, 19, 38–81.

NASH, J., J. F. (1950): "The Bargaining Problem," Econometrica, 155–162.

NGAI, L. R. AND K. D. SHEEDY (2020): "The decision to move house and aggregate housing-market dynamics," Journal of the European Economic Association, 18, 2487–2531.

——— (2024): "THE INS AND OUTS OF SELLING HOUSES: UNDERSTANDING HOUSING-MARKET VOLATILITY," International Economic Review.

NGAI, L. R. AND S. TENREYRO (2014): "Hot and cold seasons in the housing market," American Economic Review, 104, 3991–4026.

NOVY-MARX, R. (2009): "Hot and cold markets," Real Estate Economics, 37, 1–22.

O'HARA, M. AND X. A. ZHOU (2021): "Anatomy of a liquidity crisis: Corporate bonds in the COVID-19 crisis," Journal of Financial Economics, 142, 46–68.

PIAZZESI, M., M. SCHNEIDER, AND J. STROEBEL (2020): "Segmented housing search," American Economic Review, 110, 720–759.

PISSARIDES, C. A. (2000): Equilibrium Unemployment Theory, 2nd Edition, MIT Press Books, The MIT Press.

RAMANI, A. AND N. BLOOM (2021): "The Donut Effect of Covid-19 on Cities," Working Paper 28876, National Bureau of Economic Research.

ROSENTHAL, S. S., W. C. STRANGE, AND J. A. URREGO (2022): "JUE insight: Are city centers losing their appeal? Commercial real estate, urban spatial structure, and COVID-19," Journal of Urban Economics, 127, 103381.

SAFEGRAPH (2025): "Monthly Patterns [Dataset]," https://doi.org/10.82551/ST80-VH91, accessed August 31, 2025.

SMITH, E. (2020): "High and low activity spells in housing markets," Review of Economic Dynamics, 36, 1–28.

WANG, C. AND T. ZHOU (2023): "Face-to-face interactions, tenant resilience, and commercial real estate performance," Real Estate Economics, 51, 1467–1511.

WHEATON, W. C. (1990): "Vacancy, search, and prices in a housing market matching model," Journal of political Economy, 98, 1270–1292.

Online Appendix

A Proofs for Comparative Statics Results

Combining HE with PP gives an equation that determines equilibrium tightness:

$$\frac{(r+\delta)k+c_S}{\mu\theta^{1-\eta}} = \beta\frac{\varepsilon+c_B-(r+\delta)k}{r+\delta+s+(1-\beta)\mu\theta^{-\eta}},$$

$$\log((r+\delta)k+c_S)-\log\mu-(1-\eta)\log\theta =$$
$$\log\beta+\log(\varepsilon+c_B-(r+\delta)k)-\log(r+\delta+s+(1-\beta)\mu\theta^{-\eta}).$$

A.1 Drop in search efficiency μ

To find the effect on **tightness**, take the derivative of the equilibrium condition above with respect to μ:

$$\frac{(1-\beta)\theta^{-\eta}+(1-\beta)\mu(-\eta)\theta^{-\eta-1}\frac{\partial\theta}{\partial\mu}}{r+\delta+s+(1-\beta)\mu\theta^{-\eta}} = \frac{1}{\mu}+(1-\eta)\frac{\partial\log\theta}{\partial\mu}.$$

After rearranging and simplifying:

$$\frac{\partial\log\theta}{\partial\log\mu} = -\frac{r+\delta+s}{(1-\eta)(r+\delta+s)+(1-\beta)\mu\theta^{-\eta}} < 0.$$

Thus, a decrease in the search efficiency μ leads to higher tightness θ.

To calculate the effect on **prices**, log-differentiate the HE line:

$$\log(P-k) = \log((r+\delta)k+c_S)-\log\mu-(1-\eta)\log\theta,$$
$$\frac{\partial P}{\partial\log\mu}\frac{1}{P-k} = -1-(1-\eta)\frac{\partial\log\theta}{\partial\log\mu}.$$

Using the derivative of the tightness with respect to the search efficiency:

$$\frac{\partial P}{\partial \log \mu}\frac{1}{P-k} = -\frac{(1-\beta)\mu\theta^{-\eta}}{(1-\eta)(r+\delta+s)+(1-\beta)\mu\theta^{-\eta}} < 0.$$

Thus, a drop in the search efficiency increases prices.

Similarly to prices, **time on the market** increases:

$$\begin{aligned}
\textbf{TOM} &= \frac{1}{\theta m(\theta)} = \frac{1}{\mu\theta^{1-\eta}}, \\
\log \textbf{TOM} &= -\log\mu - (1-\eta)\log\theta, \\
\frac{\partial \log \textbf{TOM}}{\partial \log \mu} &= -1-(1-\eta)\frac{\partial \log\theta}{\partial \log \mu} < 0.
\end{aligned}$$

To get the effect on the sales, we need to know how **the number of buyers** changes first. We can use the Beveridge curve:

$$\begin{aligned}
b &= \frac{s+\delta}{s+\delta+\mu\theta^{-\eta}}, \\
\frac{\partial \log b}{\partial \mu} &= -\frac{\theta^{-\eta}-\eta\mu\theta^{-\eta-1}\frac{\partial\theta}{\partial\mu}}{s+\delta+\mu\theta^{-\eta}} = -\theta^{-\eta}\frac{1-\eta\frac{\partial\log\theta}{\partial\log\mu}}{s+\delta+\mu\theta^{-\eta}}.
\end{aligned}$$

Rearranging and using previous calculation for $\partial \log\theta/\partial\log\mu$ for the numerator:

$$1-\eta\frac{\partial\log\theta}{\partial\log\mu} = 1-\eta\left(-\frac{r+\delta+s}{(1-\eta)(r+\delta+s)+(1-\beta)\mu\theta^{-\eta}}\right) = \frac{(r+\delta+s)+(1-\beta)\mu\theta^{-\eta}}{(1-\eta)(r+\delta+s)+(1-\beta)\mu\theta^{-\eta}} > 0.$$

Thus, the number of buyers increases due to a reduction in the search efficiency:

$$\frac{\partial \log b}{\partial \mu} = -\theta^{-\eta}\frac{(r+\delta+s)+(1-\beta)\mu\theta^{-\eta}}{(s+\delta+\mu\theta^{-\eta})((1-\eta)(r+\delta+s)+(1-\beta)\mu\theta^{-\eta})} < 0.$$

Now we can derive the change in the **sales**:

$$\text{Sales} = bm(\theta) = b\mu\theta^{-\eta}.$$
$$\frac{\partial \log \text{Sales}}{\partial \log \mu} = \frac{\partial \log b}{\partial \log \mu} + 1 - \eta \frac{\partial \log \theta}{\partial \log \mu}.$$

$$\frac{\partial \log \text{Sales}}{\partial \log \mu} = \frac{(r+\delta+s)+(1-\beta)\mu\theta^{-\eta}}{(1-\eta)(r+\delta+s)+(1-\beta)\mu\theta^{-\eta}} \frac{(s+\delta)}{(s+\delta+\mu\theta^{-\eta})} > 0$$

The sales, thus, drop with a drop in the search efficiency.

Finally, the change in the **number of listings**, $v = b/\theta$, can be found from:

$$\frac{\partial \log v}{\partial \log \mu} = \frac{\partial \log b}{\partial \log \mu} - \frac{\partial \log \theta}{\partial \log \mu},$$

where

$$\frac{\partial \log b}{\partial \log \mu} = -\mu\theta^{-\eta} \frac{(r+\delta+s)+(1-\beta)\mu\theta^{-\eta}}{(s+\delta+\mu\theta^{-\eta})((1-\eta)(r+\delta+s)+(1-\beta)\mu\theta^{-\eta})},$$
$$\frac{\partial \log \theta}{\partial \log \mu} = -\frac{r+\delta+s}{(1-\eta)(r+\delta+s)+(1-\beta)\mu\theta^{-\eta}}.$$

$$\frac{\partial \log v}{\partial \log \mu} = -\frac{1}{(1-\eta)(r+\delta+s)+(1-\beta)\mu\theta^{-\eta}}(\mu\theta^{-\eta}\frac{(r+\delta+s)+(1-\beta)\mu\theta^{-\eta}}{(s+\delta+\mu\theta^{-\eta})} - (r+\delta+s)) =$$
$$= -\frac{1}{((1-\eta)(r+\delta+s)+(1-\beta)\mu\theta^{-\eta})(s+\delta+\mu\theta^{-\eta})}((1-\beta)(\mu\theta^{-\eta})^2 - (r+\delta+s)(s+\delta)).$$

If the tightness is high, the expression in brackets is negative; then the derivative is positive. When the search efficiency drops, the number of listings drops.

A.2 Increase in Buyer's Search Costs c_B

To find the effect on **tightness**, take the derivative with respect to c_B:

$$-(1-\eta)\frac{\partial \log \theta}{\partial c_B} = \frac{1}{\varepsilon + c_B - (r+\delta)k} - \frac{(1-\beta)\mu(-\eta)\theta^{-\eta-1}\frac{\partial \theta}{\partial c_B}}{r+\delta+s+(1-\beta)\mu\theta^{-\eta}}$$

We can find $1/(\varepsilon + c_B - (r+\delta)k)$ from the equilibrium condition:

$$\frac{\partial \log \theta}{\partial c_B} = -\frac{\beta\mu\theta^{1-\eta}}{((r+\delta)k + c_S)((1-\eta)(r+\delta+s) + (1-\beta)\mu\theta^{-\eta})} < 0$$

If the buyer's search costs increase, tightness drops.

To calculate the effect on **prices**, log-differentiate the HE line:

$$\log(P-k) = \log((r+\delta)k + c_S) - \log\mu - (1-\eta)\log\theta,$$

$$\frac{\frac{\partial P}{\partial c_B}}{P-k} = -(1-\eta)\frac{\partial \log \theta}{\partial c_B} > 0$$

When the buyer's search costs rise, prices increase as well.

Since tightness drops, the **seller's time on the market** increases $\text{TOM} = 1/(\theta m(\theta))$.

The change in **the number of buyers** can be found from the Beveridge curve:

$$b = \frac{s+\delta}{s+\delta+m(\theta)} = \frac{s+\delta}{s+\delta+\mu\theta^{-\eta}},$$

Because θ decreases, the denominator rises, and the number of buyers drops.

To get the effect on the sales, we need to know by how much the number of buyers drops:

$$\log b = \log(s+\delta) - \log(s+\delta+\mu\theta^{-\eta}),$$
$$\frac{\partial \log b}{\partial c_B} = \frac{\mu\eta\theta^{-\eta}}{(s+\delta+\mu\theta^{-\eta})}\frac{\partial \log \theta}{\partial c_B} < 0$$

The effect on **sales** depends on the relative strength of the effects on the number of buyers and tightness:

$$\text{Sales} = bm(\theta) = b\mu\theta^{-\eta},$$
$$\log \text{Sales} = \log b + \log \mu - \eta \log \theta,$$
$$\frac{\partial \log \text{Sales}}{\partial c_B} = \frac{\partial \log b}{\partial c_B} - \eta\frac{\partial \log \theta}{\partial c_B} = -\frac{(s+\delta)}{(s+\delta+\mu\theta^{-\eta})}\frac{\partial \log \theta}{\partial c_B} > 0$$

If the buyer's search costs increase, sales increase as well.

Effect on the **number of listings:**

$$\log v = \log b - \log \theta,$$
$$\frac{\partial \log v}{\partial c_B} = \frac{\partial \log b}{\partial c_B} - \frac{\partial \log \theta}{\partial c_B} = \frac{\mu\eta\theta^{-\eta}}{(s+\delta+\mu\theta^{-\eta})}\frac{\partial \log \theta}{\partial c_B} - \frac{\partial \log \theta}{\partial c_B} =$$
$$= \frac{-(1-\eta)\mu\theta^{-\eta} - (s+\delta)}{(s+\delta+\mu\theta^{-\eta})}\frac{\partial \log \theta}{\partial c_B} < 0.$$

Thus, higher buyer search costs lead to a larger number of listings.

B Additional Robustness

Table A1: Sales Prices and Sale Hazard

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	0 - 5 miles					2 - 5 miles				
	Panel A: Sales Price									
Under SAH	0.018**	0.014**	0.015**	0.025***	0.030***	0.035***	0.022**	0.018*	0.017*	0.027***
	(0.007)	(0.007)	(0.006)	(0.005)	(0.005)	(0.011)	(0.011)	(0.010)	(0.009)	(0.009)
After SAH	0.023***	0.022***	0.026***	0.035***	0.039***	0.046***	0.040***	0.036***	0.037***	0.045***
	(0.005)	(0.004)	(0.004)	(0.004)	(0.003)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)
Observations	1,056,226	1,056,226	1,056,226	1,056,142	1,054,274	309,398	309,398	309,398	309,379	308,941
R-squared	0.731	0.762	0.789	0.848	0.860	0.770	0.788	0.806	0.849	0.860
	Panel B: Sale Hazard									
Under SAH	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***	-0.006***	-0.006***	-0.006***	-0.006***	-0.006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
After SAH	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***	-0.008***	-0.008***	-0.008***	-0.008***	-0.008***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	35,229,039	35,229,039	35,229,039	35,229,036	35,229,036	10,475,461	10,475,461	10,475,461	10,475,459	10,475,459
R-squared	0.007	0.007	0.007	0.008	0.008	0.008	0.008	0.008	0.008	0.009
House characteristics	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Month x Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Infections	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Assessment value	N	N	N	N	Y	N	N	N	N	Y
County FE	Y	Y	Y	N	N	Y	Y	Y	N	N
Tract FE	N	N	N	Y	Y	N	N	N	Y	Y
Boundary FE	N	Y	Y	Y	Y	N	Y	Y	Y	Y
Border Group FE	N	N	Y	Y	Y	N	N	Y	Y	Y

Notes: 1) The table reports results for the sample of residential properties within 0-5 miles of the county border that were sold or listed between 2017 and early 2022 in Columns (1)-(5). For Columns (6)-(10), it reports results for properties within 2-5 miles of the county border. 2) The dependent variables are the logarithm of the sales price in Panel A and a dummy variable that takes a value of 1 at the sales contract date and zero otherwise in Panel B. 3) The house characteristics include distance to the Central Business District, age, age squared, log of the square footage of the living area, log of the lot size, dummies for the number of bedrooms, dummies for the number of bathrooms, categorical variables for the condition of the property, type of heating, type of air conditioning, property type, number of garage spaces, number of fireplaces, and a dummy variable indicating whether the property is newly constructed. 4) The infection variables include the number of new infections per capita and the percent change in new infections. 5) ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Table A2: Sales and Listings

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	0 - 5 miles					2 - 5 miles				
	Panel A: Sales									
Under SAH	-0.217***	-0.217***	-0.217***	-0.217***	-0.308***	-0.133***	-0.133***	-0.133***	-0.133***	-0.303***
	(0.024)	(0.024)	(0.024)	(0.023)	(0.029)	(0.039)	(0.039)	(0.039)	(0.038)	(0.053)
After SAH	-0.056**	-0.056**	-0.056**	-0.056**	-0.197***	0.018	0.018	0.018	0.018	-0.137*
	(0.026)	(0.026)	(0.026)	(0.025)	(0.038)	(0.040)	(0.040)	(0.039)	(0.039)	(0.073)
Observations	6,604,407	6,600,986	6,600,986	6,499,881	5,051,318	2,062,174	2,062,174	2,062,174	2,035,518	1,555,234
	Panel B: New Listings									
Under SAH	-0.339***	-0.339***	-0.339***	-0.339***	-0.446***	-0.218***	-0.218***	-0.218***	-0.218***	-0.396***
	(0.021)	(0.021)	(0.021)	(0.020)	(0.025)	(0.034)	(0.034)	(0.034)	(0.033)	(0.043)
After SAH	-0.173***	-0.173***	-0.173***	-0.173***	-0.401***	-0.110***	-0.110***	-0.110***	-0.110***	-0.372***
	(0.024)	(0.024)	(0.023)	(0.023)	(0.034)	(0.037)	(0.037)	(0.036)	(0.036)	(0.064)
Observations	7,008,634	7,008,634	7,008,634	6,967,094	5,801,757	2,217,390	2,217,390	2,217,390	2,196,309	1,766,996
Year x Month FE	Y	Y	Y	Y	N	Y	Y	Y	Y	N
Infections	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	N	N	Y	Y	Y	N	N
Boundary FE	N	Y	Y	Y	Y	N	Y	Y	Y	Y
Boundary Group FE	N	N	Y	Y	Y	N	N	Y	Y	Y
Tract FE	N	N	N	Y	N	N	N	N	Y	N
Tract x Year x Month FE	N	N	N	N	Y	N	N	N	N	Y

Notes: 1) The table reports results for the sample of residential properties within 0-5 miles of the county border that were sold or listed between 2017 and early 2022 in Columns (1)-(5). For Columns (6)-(10), it reports results for properties within 2-5 miles of the county border. 2) The dependent variables are the number of sales in Panel A, defined using the sales contract date, and the number of new listings in Panel B, defined using the first listing date. Both variables are calculated using the MLS sample and are measured at the census tract-by-day level. 3) The table shows the estimates from the Poisson pseudo-maximum likelihood regressions. 4) The infection variables include the number of new infections per capita and the percent change in new infections. 5) R-squared is not reported for the Poisson pseudo-maximum likelihood regressions because they are nonlinear so the residuals and predictions are not orthogonal. 6) ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Table A3: Sale Prices, Sale Hazard, Sales and Listings: Alternative Samples

	1 - 2 miles	1 - 10 miles	1 - 2 miles	1 - 10 miles
	(1)	(2)	(3)	(4)
	Panel A: Sales Price		Panel C: Sales	
Under SAH	0.050	0.032***	-0.448***	-0.248***
	(0.052)	(0.006)	(0.173)	(0.021)
After SAH	0.026	0.046***	-0.331*	-0.108***
	(0.042)	(0.004)	(0.199)	(0.022)
Observations	23,876	1,213,500	306,372	5,996,153
R-squared	0.812	0.846		
	Panel B: Sale Hazard		Panel D: New Listings	
Under SAH	-0.004*	-0.005***	-0.605***	-0.334***
	(0.002)	(0.000)	(0.174)	(0.019)
After SAH	-0.002	-0.005***	-0.452**	-0.204***
	(0.003)	(0.000)	(0.198)	(0.021)
Observations	975,831	41,196,794	313,509	6,615,633
R-squared	0.007	0.008		
Year x Month FE	Y	Y	Y	Y
House characteristics	Y	Y	N	N
Distance to CBD	Y	Y	N	N
Infections	Y	Y	Y	Y
Boundary FE	Y	Y	Y	Y
Boundary Group FE	Y	Y	Y	Y
Tract FE	Y	Y	Y	Y

Notes: 1) The table reports results for residential properties within 1-2 miles of the county border that were sold or listed between 2017 and early 2022 in Columns (1) and (3). For Columns (2) and (4), it reports results for properties within 1-10 miles of the county border. 2) The dependent variables in all Panels are defined the same as in Tables 2 and 3. For property-level samples in Panels A and B, the same house characteristics and distance to the CBD as in Table 2 are included as controls. 3) Panels C and D report the estimates from the Poisson pseudo-maximum likelihood regression. 4) The infection variables include the number of new infections per capita and the percent change in new infections. 5) R-squared is not reported for the Poisson pseudo-maximum likelihood regressions because they are nonlinear so the residuals and predictions are not orthogonal. 6) ***, **, and * denote significance at the 1%, 5%, and 10% levels.

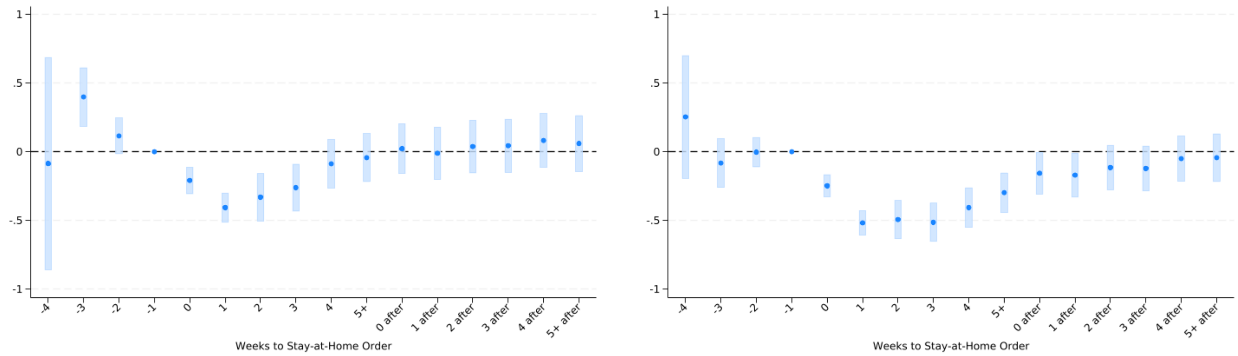
Table A4: Comparison of house characteristics across the county border

Characteristic	(1)	(2)
	underSAH	afterSAH
Ln(Lot Size)	0.044	0.002
	(0.027)	(0.007)
Ln(Living SF)	0.020	0.001
	(0.012)	(0.003)
Age	-0.887	0.040
	(0.674)	(0.171)
Distance to CBD	0.116	0.364
	(0.997)	(0.254)
Bedrooms	0.033	0.004
	(0.028)	(0.007)
Bathrooms	-0.072***	-0.060***
	(0.022)	(0.006)

Notes: 1) The table reports results for the sample of residential properties within 1-5 miles of the county border that were sold or listed between 2017 and early 2022. 2) A unit of observation is a transaction. 3) The coefficients are from regressions of a house characteristic on the interaction of the border dummy and underSAH dummy in column (1) and on the interaction of the border dummy and afterSAH dummy in column (2). The regression control for year x month, border, and border group fixed effects. 5) ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Figure A1: Dynamic Effects on Sales and Listings: Robustness

(a) Sales (b) New Listings



Notes: 1) The panels show point estimates from the Poisson pseudo-maximum likelihood regression and 95% confidence intervals from event studies in (4). The period before the start of the SAH is the ommited period. 2) The figures report results for the sample of residential properties within 1-5 miles of the county border that were sold or listed between 2017 and early 2022. 3) The figures report results from the specification with census tract-by-month fixed effects. 4) The dependent variables are the number of sales in figure (a), defined using the sales contract date, and the number of new listings in figure (b), defined using the first listing date. Both variables are calculated using the MLS sample and are measured at the census tract-by-day level. 5) The same infection variables as in Table 3 are included as controls.

Table A5: Sale Prices, Sale Hazard, Sales and Listings: Robustness

	(1)	(2)	(3)	(4)	(5)
	Panel A: Sales Price				
Under SAH	0.046***	-0.002	0.027***	-0.017***	-0.003
	(0.005)	(0.005)	(0.005)	(0.005)	(0.031)
After SAH	-0.010**	0.023***	-0.023***	-0.000	-0.001
	(0.005)	(0.004)	(0.005)	(0.006)	(0.030)
	Panel B: Sale Hazard				
Under SAH	-0.001	-0.002***	0.000	-0.001**	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)
After SAH	-0.002***	-0.003***	-0.000	-0.001**	-0.001
	(0.001)	(0.000)	(0.000)	(0.000)	(0.003)
	Panel C: Sales				
Under SAH	0.065***	0.018	0.060**	0.002	-0.035
	(0.025)	(0.024)	(0.025)	(0.026)	(0.059)
After SAH	0.029	-0.008	0.010	-0.046	-0.020
	(0.032)	(0.029)	(0.033)	(0.031)	(0.062)
	Panel D: New Listings				
Under SAH	-0.096***	-0.031	-0.108***	-0.057**	-0.062
	(0.023)	(0.022)	(0.023)	(0.023)	(0.062)
After SAH	-0.130***	-0.048*	-0.155***	-0.095***	-0.051
	(0.028)	(0.026)	(0.028)	(0.029)	(0.065)
Specification	SAH in 2018	SAH in 2019	SAH in 2018	SAH in 2019	Random dates
Drop obs after 2020?	No	No	Y	Y	No
Year x Month FE	Y	Y	Y	Y	Y
Infections	Y	Y	N	N	Y
Boundary FE	Y	Y	Y	Y	Y
Boundary Group FE	Y	Y	Y	Y	Y
Tract FE	Y	Y	Y	Y	Y

Notes: 1) The table reports results for residential properties within 1-5 miles of the county border. 2) The dependent variables in all Panels are defined the same as in Tables 3 and 4. For property-level samples in Panels A and B, the same hedonic characteristics and distance to the CBD as in Table 3 are included as controls. 3) Panels C and D report the estimates from the Poisson pseudo-maximum likelihood regression. 4) The infection variables include the number of new infections per capita and the percent change in new infections. 5) ***, **, and * denote significance at the 1%, 5%, and 10% levels.