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How much did pandemic uncertainty affect real-estate speculation? Evidence from on-market valuation of for-sale versus rental properties

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ABSTRACT

We exploit a panel of Zillow Inc. property valuations to estimate the excess real-estate price growth observed in three California cities that is attributable to speculation triggered by the COVID-19 pandemic. Our research design leverages the counterfactual comparison of properties listed for sale to properties listed for rent, with the latter property class being available for habitation – just not for purchase – and thus neutral to price speculation. We implement a pre/post-2020 difference-in-difference estimation, which utilizes unit-level matching of otherwise similar sale and rental properties within a 1/2-mile radius of each other to compare differences in (a) 1-month valuation changes and (b) spot valuation uncertainties. Results indicate post-2020 property valuations in Merced and San Jose featured an excess annual price estimate growth of 22% and 14.8% points, respectively, whereas the Fresno market does not feature statistically significant excess growth.

KEYWORDS

COVID-19; quasi-experiment; difference-in-difference; unit-level matching; real-estate; speculation; excess price growth

JEL CLASSIFICATION

R21; R31; D83; L85; G14

I. Introduction

The COVID-19 pandemic was a sudden shock to global society, with implications extending well beyond individual and collective health concerns, as the magnitude and duration of the shock impacted many aspects of individual life-course decision-making. Yet despite heightened uncertainty and volatility in US financial and real-estate markets, house prices appreciated across the US in 2021, growing by roughly 23% in California.

Against this backdrop, we seek to estimate the excess real-estate price growth observed in three California cities (San Jose, Fresno and Merced) attributable to speculation – defined as near-term expectations of price and price movements (Malpezzi and Wachter 2005) – triggered by the COVID-19 pandemic. These cities belong to the Bay Area megaregion, such that the driving time between San Jose and Fresno (Merced) is roughly 2.5 hours (respectively, 2 hours). According to the 2020 US census, the population density is highest in San Jose (5,680 people/mile^2), and lowest in Merced (3,710 people/mile^2), with Fresno at the midpoint. Despite variable socio-economic development within and across each city, these cities share a common regulatory backdrop and a pervasive short supply of affordable housing (Raetz et al. 2020).

Hence, to measure the effect of pandemic uncertainty on real-estate valuations, we constructed a city-level panel comprised of individual property estimates from 2018 to 2021, which facilitates a matched-pair difference-in-difference strategy. Specifically, we compare otherwise similar on-market sale and rental properties within a 1/2- mile radius of each other, where the latter property type serves as a counterfactual that is neutral to real-estate speculation. This approach is analogue to price-to-earnings ratio methods used to identify atypical real-estate valuation regimes and contributes to research on inelastic supply, speculation and bubble formation (Glaeser, Gyourko, and Saiz 2008; Hong, Scheinkman, and Xiong 2008; Malpezzi and Wachter 2005; Petersen 2022; Roehner 2002; Shiller 2015).

II. Methodology

Data collection and property-level measures

Our primary source data are individual property valuation estimates obtained from Zillow.com, the

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most prominent US real-estate platform, with data on roughly 75% of the 142 million housing units tracked by the US Census Bureau in 2021 (ZillowInc 2016). This platform facilitates constructing near-comprehensive snapshots of regional housing markets, with the advantage that spot price estimates of individual properties are algorithmically consistent. Zillow also provides two unique metrics that are critical for understanding price speculation: (a) the 30-day change in spot price estimate and (b) the nominal uncertainty in spot price estimate.

We collected comprehensive on-market snapshots from Zillow.com for each city on a monthly basis from March 2018 to September 2021, totalling 44,635 properties' listings belonging to two property types ('For Sale' and 'Rent'), grouped by two sampling periods ('before 2020' or 'after 2020'). For each property listing h sampled in month m, we obtained its longitude and latitude; its Zillow price estimate (Zestimate®, denoted by $P_{h,m}$); a high and low range for the Zestimate®, denoted by $P^{+}_{h,m}$ and $P^{-}_{h,m}$, respectively; and the nominal change in $P_{h,m}$ over the previous 30-day period, denoted by $\delta P_{h,m}$. Note that $P_{h,m}$ incorporates property-level information (such as housing unit size, construction date and materials, garage capacity, school district, etc.) and platform-derived information (such as page views and contemporaneous neighbourhood sales activity). We also computed two additional percentage-oriented metrics: (a) the 30-day percent price change, $\Delta P_{h,m} = 100 \times \delta P_{h,m} / \left(P_{h,m} - \delta P_{h,m}\right)$; and (b) the percent uncertainty, $U_{h,m} = 100\left(P^{+}_{h,m} - P^{-}_{h,m}\right)/P_{h,m}$. All price values were first deflated to 2018 US$; for additional details and motivation behind the data collection, see Petersen (2022).

Property-level matching

We employ unit-level matching to optimize counterfactual measurement precision. As such, our difference-in-difference (DiD) strategy accounts for unobserved unit-level features (Stuart 2010), addresses the high degree of within-city price and price change variation, and leverages consistent data generated by a single pricing algorithm.

Figure 1(c) illustrates the matching procedure, whereby each property h listed for sale is matched to its most similar neighbouring properties listed for rent based upon three features: (i) price strata; (ii) listing month; and (iii) geographic location. For (i) we constrained matched property valuations to be within ± 1 decile group $Q_c\left(P_{h,m}\right)$, with 1 (respectively, 10) representing the lowest (highest) price decile specific to city c and time period. For (ii) we constrained listing dates to be within 2 months to account for intra-year demand cycles. For (iii) we constrained locations within a 1/2 mile to ensure common access to local amenities (schools, grocery stores, etc.).

For each h we then estimate its counterfactual $\Delta P_{h,m}$ and $U_{h,m}$ values had it instead been listed for rent. For brevity, we represent either $\Delta P_{h,m}$ or $U_{h,m}$ by the variable Y. Thus, for each h and $Y_{h|\text{For Sale}}$ value, we calculated the average value, $\langle Y \rangle_{\{m_h\}|\text{Rent}}$, across the set of matched houses, denoted by $\{m_h\}$. For robustness, we only analyse h with ≥ 4 rental matches. The counterfactual difference is

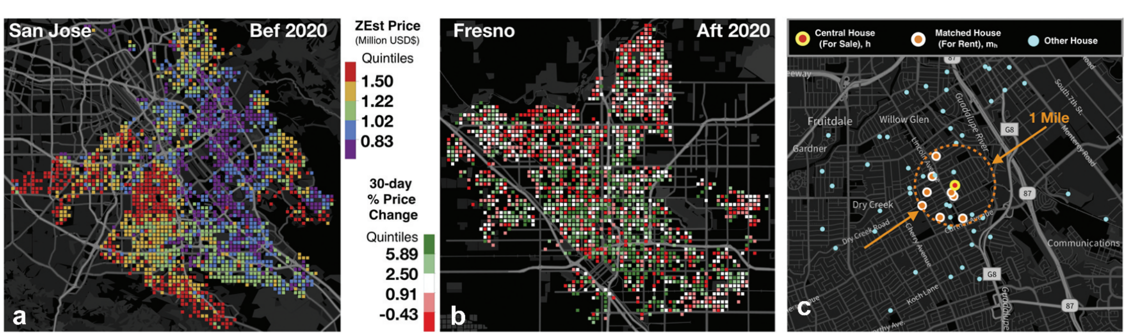

Figure 1. (a) Distribution of Zillow property value estimates (Zestimate®, P_h) across San Jose. Each grid shows the average P_h calculated for on-market properties before 2020, with colour corresponding to price quintile. (b) Average 30-day price estimate change (ΔP_h) in Fresno. (c) High spatiotemporal data resolution facilitates matching of similar on-market sale and rental properties within a 1/2-mile radius; blue dots indicate candidate properties from the same period that do not meet matching criteria.

$$\Delta_{Y,h} = Y_{h|\text{For Sale}} - \langle Y \rangle_{\{m_h\}|\text{Rent}}, \quad (1)$$

and the average $\Delta_{Y,h}$ calculated across all h in city c is denoted by $\bar{\Delta}_{Y,c}$. In total, we obtained 12,304 matched h; by city [San Jose, Merced, Fresno] and period, we obtained [5113, 246, 265] (after 2020) and [4363, 1763, 554] (before 2020) matched observations. The averages calculated for data before 2020 (respectively, after 2020) are denoted by $\bar{\Delta}_{Y,c,Bef}$ (respectively, $\bar{\Delta}_{Y,c,Aft}$). Hence, the DiD estimator is given by

$$\Delta\bar{\Delta}_{Y,c} = \bar{\Delta}_{Y,c,Aft} - \bar{\Delta}_{Y,c,Bef}. \quad (2)$$

III. Results

Estimating excess price growth attributable to pandemic uncertainty

The magnitude and statistical significance of $\bar{\Delta}_{Y,c}$ and $\Delta\bar{\Delta}_{Y,c}$ measure the degree to which shifts in real-estate valuation are attributable to shifts in market speculation exacerbated by COVID-19 pandemic uncertainty. We evaluate $\bar{\Delta}_{Y,c}$ using Student's T-test, and $\Delta\bar{\Delta}_{Y,c}$ using the two-sample Student's T-test with Welch correction.

Figure 2 shows the magnitude and statistical significance of $\bar{\Delta}_{Y}$ and $\Delta\bar{\Delta}_{Y,c}$ calculated for $\Delta P_{h,m}$ and $U_{h,m}$. Using San Jose as example, Figure 2(b)

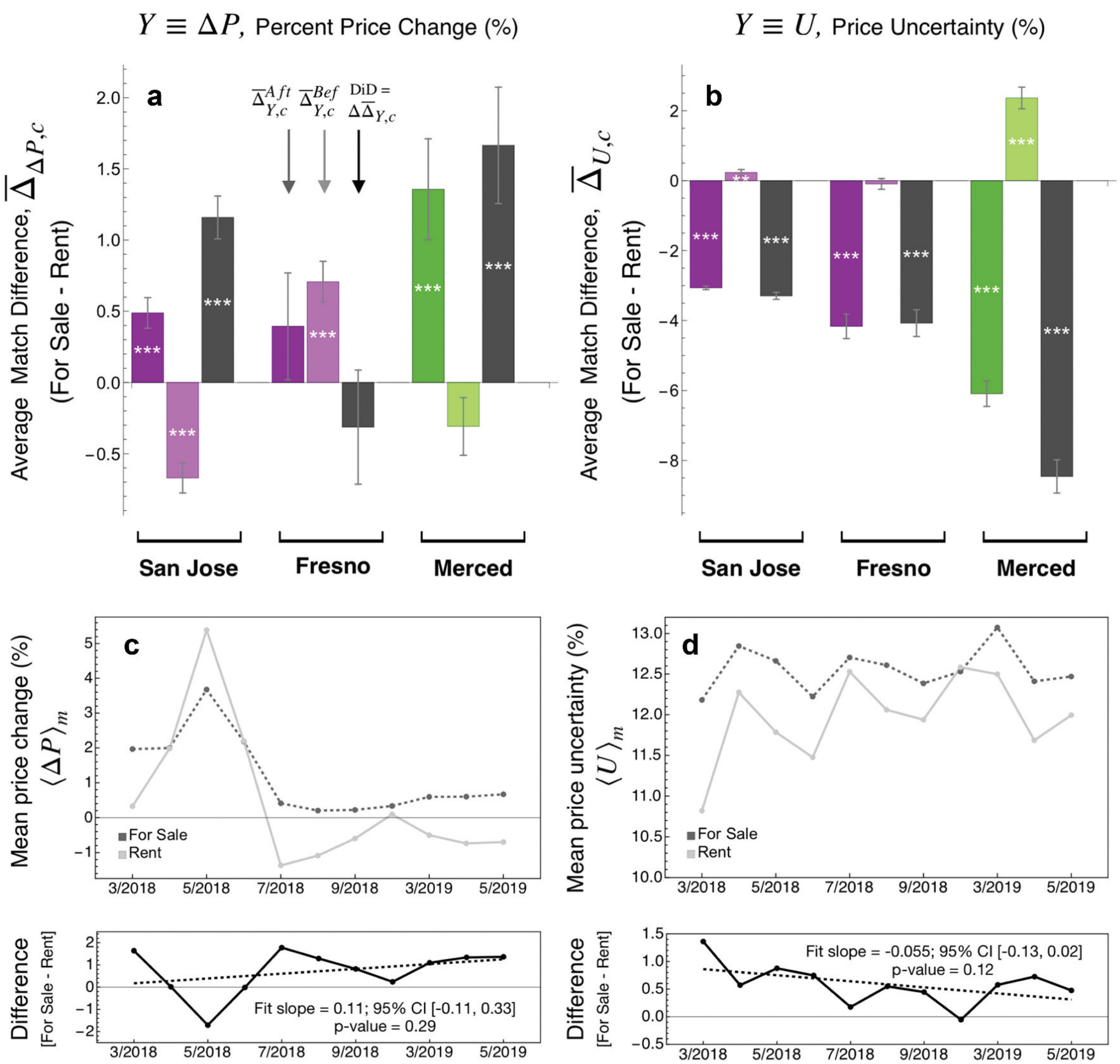

Figure 2. Estimation of housing market valuation shifts attributable to COVID-19. (a,b) Colours indicate large (magenta) versus small cities (green), defined by their population size. For each city, the first (second) bar is the average match difference after 2020 (before 2020), denoted by $\bar{\Delta}_{Y,c,Aft}$ ($\bar{\Delta}_{Y,c,Bef}$). Each grey bar represents the difference-in-difference $\Delta\bar{\Delta}_{Y,c} \equiv \bar{\Delta}_{Y,c,Aft} - \bar{\Delta}_{Y,c,Bef}$. Error bars indicate the standard error of the mean, and stars indicate the T-Test significance level: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. (c,d) Monthly pre-pandemic trend by property type (top panels). Data satisfy the parallel trend assumptions, demonstrated by calculating the difference between the two property types and performing a linear OLS regression, which indicates no significant trend (bottom panels).

indicates an average excess monthly percent price change of $\bar{\Delta}_{\Delta P,Aft}$= +0.49% (respectively, $\bar{\Delta}_{\Delta P,Bef}$ = −0.67%); hence, $\Delta\bar{\Delta}_{\Delta P} = 1.16\%$. Similarly, Figure 2(c) shows a decrease in price uncertainty after 2020, with $\bar{\Delta}_{U,Aft} = -3.1\%$ and $\bar{\Delta}_{U,Bef} = 0.23\%$; hence, $\Delta\bar{\Delta}_{U} = -3.3\%$.

Comparing results across cities, we observe two general patterns. First, we report a divergence in counterfactual valuations after 2020, $\bar{\Delta}_{\Delta P,Aft} > 0$. For the two cities with robust rental markets, namely San Jose (a prominent startup hub featuring high employment turnover) and Merced (a nascent college town), the sign of $\Delta P_{h,m}$ differed before and after 2020, which may reflect differential remote accommodation opportunities and urban amenity demand. Extrapolating $\Delta\bar{\Delta}_{\Delta P}$ to annual growth rates, results indicate that Merced and San Jose properties featured an excess annual price growth of 22% and 14.8% points, respectively.

Second, we observe a counterintuitive increase in price certainty following the shock to global socio-economic uncertainty, $\bar{\Delta}_{U,Aft} < 0$. Moreover, $\Delta\bar{\Delta}_{U} < 0$ vary from −3% (San Jose) to −8% points (Merced).

IV. Discussion and conclusion

This work contributes to real-estate market literature leveraging the pandemic as a natural experiment (Balemi, Füss, and Weigand 2021; D'Lima, Lopez, and Pradhan 2022; Fu, Jin, and Liu 2022; Fukuda 2022; Liu and Su 2021; Mondragon and Wieland 2022; Petersen 2022), and highlights opportunities to construct high-resolution market snapshots by web-scraping real-estate platform listings (Bricongne, Meunier, and Pouget 2023; Fu, Jin, and Liu 2022; Pangallo and Loberto 2018; Petersen 2022). For example, Bricongne et al. (2023) use property listing page-view metrics combined with property sales data to identify the emergence of 'wait-and-see' behaviour accompanied by listing price decreases following the onset of the pandemic in London, UK.

Here, we compared consistent property valuations across two property classes, both before and after 2020, and identify a significant excess price growth and uncertainty reduction attributable to speculative market reaction to the COVID-19 pandemic in California, USA. Our two main results – namely, excess price growth and price-uncertainty reduction – are perplexing given the heightened levels of uncertainty caused by the pandemic, even when accounting for reduced borrowing costs and crisis management policy implemented over the same period (Petersen 2022). Yet when considered from the home-buyer perspective (Huck, Mesly, and Afawubo 2022), these counter-intuitive shifts are nevertheless supported by behavioural science research showing that uncertainty (Tormala 2016) and sudden unexpected interruptions (Kupor and Tormala 2015) can be persuasive decision-making factors.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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