Centre for Economic Performance

Discussion Paper ISSN 2042-2695

No.1793
September 2021

The donut effect of Covid-19 on cities

Nicholas Bloom
Arjun Ramani

THE LONDON SCHOOL OF ECONOMICS AND POLITICAL SCIENCE
30 YEARS CEP
UKRI Economic and Social Research Council

Abstract
Using data from the US Postal Service and Zillow, we quantify the effect of Covid-19 on migration patterns and real estate markets within and across US cities. We find two key results. First, within large US cities, households, businesses, and real estate demand have moved from dense central business districts (CBDs) towards lower density suburban zip-codes. We label this the "Donut Effect" reflecting the movement of activity out of city centers to the suburban ring. Second, while this observed reallocation occurs within cities, we do not see major reallocation across cities. That is, there is less evidence for large-scale movement of activity from large US cities to smaller regional cities or towns. We rationalize these findings by noting that working patterns post pandemic will frequently be hybrid, with workers commuting to their business premises typically three days per week. This level of commuting is less than pre-pandemic, making suburbs relatively more popular, but too frequent to allow employees to leave the cities containing their employer.

Key words: Covid-19, US, 'Donut Effect', migration patterns, firm-specific shocks, earnings

We are grateful to Pete Klenow and Marcelo Clerici-Arias for helpful discussions and to Saketh Prazad for excellent research assistance. We thank Nadia Evangelou for help locating the USPS data and Yichen Su, Sitian Liu, Rebecca Diamond, Isaac Sorkin, Jean-Felix Brouillette, Melanie Wallskog, Rose Tan, Franklin Xiao, Megha Patnaik, Eduardo Laguna, Nano Barahona, and Nina Buchmann for comments on earlier versions of this project. We thank the Kauffman Foundation and Stanford University for financial support
Nicholas Bloom, Stanford University and Centre for Economic Performance, London School of Economics. Arjun Ramani, Stanford University.

This paper was produced as part of the Centre's Growth Programme. The Centre for Economic Performance is financed by the Economic and Social Research Council.

Published by
Centre for Economic Performance
London School of Economics and Political Science
Houghton Street
London WC2A 2AE

1 Introduction

Since the inception of the internet, many have predicted that working-from-home (WFH) would rapidly grow and end the dominance of cities in America's economic geography. Instead, the opposite occurred. WFH gradually rose for the first two decades of the 21st century, but American 'superstar' cities like New York and San Francisco also grew. In the past year, news outlets have made similar predictions. *The Atlantic* postulated "the decline of the coastal superstar cities" and the "rise of the rest" going as far as to say that "the next Silicon Valley is nowhere." To what extent are such theories true?

Our goal in this paper is to determine how Covid and the rise of WFH have affected migration patterns and real estate markets within and across US cities. We pay particular attention to Central Business Districts (CBDs), areas like Manhattan in New York with a high concentration of business activity and population density. In theory, WFH enables an employee to live further away from their place of work by reducing or eliminating commutes. For example, one could more easily work a high-paying job based in New York City while living in a cheaper suburb or even another state. Thus, the rise of WFH should reshape migration patterns and consequently the demand for real estate across different locations. To test this theory, we measure real estate rents and prices using data from the Zillow Group and migration patterns using the National Change-Of-Address (NCOA) dataset from the United States Postal Service (USPS).[1] We draw two main sets of findings from the data.

Our first result is that real estate demand as measured by rents or prices reallocates away from major city centers towards lower density areas on the outskirts of cities in a phenomenon we call the "donut effect".[2] This alludes to the hollowing out of the city center and the rise of the surrounding suburbs like the shape of a donut. Rental rates in the central business districts (CBDs) of the largest 12 US metros have fallen almost 20 percentage points relative to the change in the bottom 50% of zip codes by population density.[3] Similarly, home price growth in CBDs have realized losses of around 15 percentage points compared to changes in such low-density zip codes.

Migration patterns as measured by the USPS show a similar pattern of reallocation. CBDs of the top 12 US cities have seen net population and business outflows cumulating to about 15% of their pre-pandemic levels. In contrast, the bottom 50% of zip codes by density have gained about 2% of their pre-pandemic stock for population and businesses.

This donut effect is primarily a large city phenomenon. Outside of the twelve largest metro areas by population, we do not observe much price growth divergence or difference in population or business outflow between the CBD and lower density zip codes. The donut effect is more

[1] Our data and replication code are available to other researchers at https://github.com/arjunramani3/donut-effect.

[2] We decided to label this a "Donut effect" rather than a "Doughnut effect" for brevity, noting the variations in usage across American vs British English (traditionally American being the former and British the later).

[3] The donut effect is more pronounced in larger cities (See Figure 4). We therefore limit the baseline results to the twelve largest Metropolitan Statistical Areas (MSAs) in the US by population which are New York, Los Angeles, Chicago, Dallas, Houston, Miami, Philadelphia, Washington DC, Atlanta, Boston, San Francisco, and Phoenix.

widespread when measured through rents but is still primarily a large-city phenomenon. The top 12 cities as measured by population see the strongest donut effects, the next 13-50 cities see smaller effects, while the remaining 51 to 365 cities see little to no effects.

Second, though we observe a *within*-metro reallocation in economic activity, we observe much less *between*-metro reallocation in activity. Indeed, metro-level regressions show that price growth was actually stronger in denser metros. Change-of-address data on the other hand show some movement across metros from denser metros to sparser metros, but this movement is quantitatively small relative to the within-metro movement from city centers to their suburbs. Overall, this finding suggests that the rise of so-called "Zoom Towns", smaller cities across America that have been marketed as remote work hubs, may not represent a broader long-term trend in the data.[4]

To interpret our data, we build a simple spatial equilibrium model with two metro areas, each containing a city center and a suburb. We introduce both hybrid-WFH and full-time WFH to the model and find that hybrid-WFH generates predictions more in tune with the data than full-time WFH. This is because hybrid-WFH allows employees to move further from their place of work, such as from a city center to a surrounding suburb. But it does not allow an employee to move to another metro area entirely because they must still commute to work on some days.

Our study relates to a growing literature on Covid, WFH, and real estate markets. A first strand of papers looks at the impact of WFH during Covid. Several papers calculate the share of jobs that can be done from home by occupation or industry (e.g., Dingel and Neiman 2020 and Mongey, Pilossoph and Weinberg 2020). Several other papers have calculated the share of workers actually working-from-home during Covid (Barrero, Bloom, and Davis 2020, Brynjolfsson et al. 2020, DeFilipis et al. 2020, and Bick et al. 2020) or have surveyed managers about remote work (Ozimek, 2020a). De Fraja, Matheson, and Rockey (2020) look at the incidence of WFH across geographies in the UK. Finally, a set of papers examine how WFH impacts productivity and find generally positive effects though there is substantial variation across workers (e.g., Bloom et al., 2015 and Emmanuel and Harrington, 2020).

A second set of papers builds spatial equilibrium models to model the impacts of WFH. Delventhal, Kwon, and Parkhomenko (2021)'s model finds that jobs move to city centers even as residents themselves move away from cities. Behrens, Kichko, and Thisse (2021) find that the demand for office space falls while the demand for living space increases, while Davis, Ghent, and Gregory (2021)'s model finds that the elasticity of substitution between in-person work and WFH has changed in favor of WFH. Previous papers have also examined how productivity spillovers and amenities lead to clustering in cities, especially of skilled workers (e.g. Albouy 2016, Diamond 2016, Gyouko, Mayer, and Sinai 2013). Couture et al. (2019) examine how amenities also respond to this clustering of workers, and Leamer and Storper (2014) discuss how IT affects economic geography.

The most similar papers to our work empirically examine how Covid has impacted real estate and migration. Su and Liu (2020) find that the demand for housing in dense locations has fallen relative to demand in less dense locations and build a general equilibrium model to explain these

[4] See Florida and Ozimek (2021) in the *Wall Street Journal* for the full essay.

phenomena. Gupta et al. (2021) similarly find a flattening of the bid-rent curve in the top 30 US metros. They find larger effects in metros with more WFH or lower housing supply elasticity and impute future rental growth implied by property price changes. Brueckner, Kahn, and Lin (2021) also document the reduction in home price gradients throughout the pandemic and model how WFH enables people to move to high-amenity locations. Rosenthal, Strange, and Urrego (2021) examine commercial real estate rents and find a reduction in rents in density locations, while Ling, Wang, and Zhou (2020) document a drop in commercial real estate prices in areas more exposed to Covid. Couture et al. (2021) use cell-phone data and find an outflow of people from New York City. Haslag and Weagley (2021) use cross-state moving data from a moving company and find a movement of mostly high-income people to smaller, less costly cities. Ozimek (2020b) find in survey data that remote work has increased the number of planned moves with more than half of survey respondents looking for more affordable housing.

Our findings complement the previous findings while addressing several previously unexplored questions. First, we utilize US Postal Service change-of-address data to measure migration flows whereas previous research has used cell-phone data, which is more likely to contain temporary moves, or moving company data, which is limited to cross-state moves. Second, we examine heterogeneity across the full set of US metros whereas previous studies have focused on a smaller subset or have not looked at heterogeneity. Third, we show that while people, businesses, and real estate demand reallocate from city centers to suburbs *within* metros, there is a less substantial reallocation *across* metros. We interpret this finding to be consistent with a post-Covid equilibrium of *hybrid* WFH as opposed to full-time WFH.

The rest of our paper is organized as follows: Section 2 describes our data and Section 3 documents our main results for both real estate markets and migration patterns. Section 4 outlines a simple model of both hybrid and full-time WFH and Section 5 concludes. We leave robustness checks, additional charts, and the full model derivation for the Appendix.

2 Data

2.1 Zillow Price Indices

We use Zillow's Observed Rental Index (ZORI) to measure changes in residential property rental rates at the zip code and MSA levels. The rent index is constructed by tracking rent changes for properties that remain listed across multiple periods. This repeated-rent methodology is similar to repeat-sales methodologies used to construct price indices as in Wallace and Meese (1997). In order to adjust for potential bias due to compositional shifts in listed properties, Zillow reweights properties based on construction year, structure type, and rental year. Currently, ZORI is only provided for the 100 largest US metros.

We also use Zillow's Home Value Index (ZHVI) to measure changes in residential property values at the zip code and MSA levels. The level of the price index is calculated by taking an average of Zillow's Zestimate across all single-family homes in a given geographic area, where the Zestimate is supposed to be a real-time reflection of property's value. Zillow employs a hedonic model to estimate home values for periods in which a property does not sell. The growth in the price index is calculated by taking the value-weighted price appreciation of all properties in a given geography. Zillow value-weights in order to capture the growth of the overall value of the housing market. The ZHVI is offered for almost the full universe of US metro areas.[5]

2.2 USPS National Change of Address (NCOA) Dataset

To directly observe migration patterns, we utilize the United States Postal Service's National Change of Address (NCOA) dataset. We submitted a Freedom of Information Act (FOIA) request to obtain zip code-month level inflow and outflow data for the universe of US zip codes over the last four years.[6] There are multiple types of change-of-address requests. To construct our measure of population inflows and outflows, we multiply the number of household change-of-address requests by 2.5, the mean household size in the US, and add the number of individual change-of-address requests. Because the USPS does not specify whether household moves are exclusive of single-person households, we conservatively report results using the average household size value that includes single-person households of 2.5. Using the average size of non-single-person households, 3.2, strengthens the main results.[7] The data also bottom-codes zip code-month flow counts to 0 if the true value is less than or equal to 10 due to privacy concerns. We impute such values to the midpoint value, 5, though our results are robust to leaving them at 0.

2.3 Working from home (WFH) exposure

We construct a zip code level measure of the share of jobs that can be done from home (WFH exposure). An important difference from other studies is our measure uses the work industries for the *residents* of a zip code as opposed to the businesses located in the zip code. This enables us to more directly observe the exposure of a zip code to current residents changing their housing demand for their current place of residence in response to the pandemic and WFH. We obtain the job industry distribution for residents across US zip codes from the LEHD Origin-Destination Employment Statistics (LODES) at the US Census Bureau[8]. LODES data is available at the census block level so we crosswalk to the zip code level. Finally, we merge the LODES data with Dingel and Neiman (2020)'s data on the share of jobs that can be done from home at the 2-digit NAICS level.

2.4 Central Business Districts (CBDs)

We map zip codes to their corresponding metro area's central business district (CBD) using data from Holian (2019). The paper compares several different sources and methods for defining CBD coordinates and concludes that the 1982 Census of Retail Trade's official coordinates best fit the point of maximum agglomeration in a city. Since the 1982 Census of Retail Trade only defines CBD coordinates for 268 metros, we define the CBDs for remaining metros using a city's City Hall – for metros where both exist, the City Hall coordinates generally track the 1982

[5] More on the index methodologies employed by Zillow can be found at https://www.zillow.com/research/data/
[6] The USPS data for recent years is now publicly available at: https://about.usps.com/who/legal/foia/library.htm
[7] Household size data is from the US Census Bureau: https://www.census.gov/data/tables/time-series/demo/families/households.html
[8] See https://lehd.ces.census.gov/data/

Census CBD coordinates. We define the area of a CBD to be all zip codes with centroids within two kilometers of the CBD coordinates. The main results are robust to alternate CBD radius distances from 1-5 kilometers.

2.5 Other zip code and MSA level characteristics

We calculate population density using population level data from the 2015-2019 American Community Survey (ACS) pooled estimates taken from IPUMS (Manson et al., 2020). Land area data is taken from Census Bureau's Zip Code Tabulation Area files.[9] We filter out all zip codes with less than 100 people or less than 0.1 sq mile of area for all of our analysis, though our results are robust to the inclusion of these zip codes. We obtain zip code latitude and longitude coordinates from the Census Bureau's Gazetteer files and use these coordinates to calculate distance from the corresponding CBD.[10] Finally, we obtain business establishment stock data from the Census Bureau's 2018 Zip Code Business Patterns dataset.[11]

3 Results

Our primary goal in this section is to characterize changes in migration patterns and real estate markets both within and across US cities since the advent of Covid-19. We focus on zip-code level factors that mediate the impact of Covid on real estate markets and migration patterns including population density, distance of the zip code from the CBD, and the ability for residents of the zip code to WFH.

3.1 Documenting the donut effect in real estate markets

Figure 1 shows the headline finding of a "donut effect" for the largest 12 US metros in the residential rental market. We plot a population weighted-average of zip code level rental indices bucketed into four groups: the central business district (CBD) and three groups of zip codes grouped by population density.[12] Here and elsewhere, the three groups are given by high = top 10%, mid = 50-90th percentile, and low = 0-50th percentile. For rental rates and home values there is a generally parallel trend of gradual growth across groups in the years preceding the Covid shock. The parallel trend suggests that post February 2020 divergence in outcomes across the four groups of zip-codes is a result of the impact of the pandemic. The CBD home value series sees a slight decline in value pre-pandemic that continues post-pandemic.

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[9] See https://www2.census.gov/geo/docs/maps-data/data/rel/

[10] See https://www.census.gov/geographies/reference-files/time-series/geo/gazetteer-files.html

[11] See https://www.census.gov/data/developers/data-sets/cbp-nonemp-zbp/zbp-api.html

[12] We normalize all indices to Feb 2020 = 100 after aggregating within each group. We aggregate first and then normalize because then the price growth of our aggregated index is weighted both by population (a proxy for the number of housing units) and the typical home value in a region (the level of the home value index). This approach allows us to capture the growth of the overall housing market in a region and is similar to how Zillow constructs its home value index. See Hryniw (2019) for more details on how Zillow value-weights in its index construction. As a robustness check, we try normalizing each index to Feb 2020 = 100 and then taking a population-weighted average across zip codes, which removes the value-weighting (See Appendix A3). The pattern of rent growth divergence and price growth divergence post-Covid is generally preserved though the effect becomes smaller for prices. The smaller effect absent value-weighting can be rationalized by noting that high-value regions suffered greater shocks since individuals who can WFH are generally skilled high-income workers (Althoff et al., 2020).

After the Covid shock, we see a substantial divergence between the CBD and low-density groups. Indeed, the difference in rent growth (Figure 1a) between the CBD and the low-density group is approximately 20 percentage points by Jan 2021. The rental indices display a striking drop starting in March 2020 that aligns with the start of Covid lockdowns and the shift to WFH in the US. Though the rental indices have started to increase across groups since Feb 2021 due to the reopening, the divergence has mostly persisted.[13]

Residential property prices show a similar divergence after the pandemic (Figure 1b) as measured by Zillow's home value index. After February 2020 the CBD and high-density group diverge substantially from the mid and low-density group. The price growth gap reaches almost 15 percentage points by March 2021. The smaller difference in the level of price growth compared to the rental growth indicates that the market expects the magnitude of the gap in rent growth to fall.[14]

Though there is reallocation in demand across density groups, it is worth noting that Covid has also increased demand for housing in the aggregate by both increasing the demand for space (Emmanuel and Harrington, 2020), and also making the cost of home-financing cheaper due to lower interest rates (Zhao, 2020). This may explain part of the upward trend across series for home prices compared to rents. The continued decline in home values for the CBD is the lone exception to this aggregate upswing in the housing market.

To determine that factors that explain the donut effect, we run zip-code level regressions with MSA fixed effects of the percent change in rent or price index from the Feb 2020 to Feb 2021 on a set of zip-code level characteristics as specified in the following equation.

$$\%\,\Delta\, price_{i,t} = \alpha + \beta_1\,\%\Delta\, price_{i,t-1} + \beta_2 \ln density_i + \beta_3 \ln dist\_CBD_i + \psi_m + \epsilon_i \quad (1)$$

Here, *i* indexes the zip code, *m* indexes the MSA, and % $\Delta Price$ is calculated by using the arc-percentage change methodology from Davis, Haltiwanger, and Schuh (1996). This method takes the percent change over the midpoint of the start and end-point values.[15]

Columns (1) to (4) of table 1 show rents fall relatively more in zip-codes with greater density, greater WFH share, and lesser distance to the CBD. These findings, which show the donut effect

[13] Here, we draw an inference from rental or price movements to a shift in demand for a location by making the assumption that housing supply is inelastic in the short-run. This assumption may be less true in the longer-run because real estate developers can respond to changes in demand, but there is some evidence that even over longer time horizons housing supply is inelastic. For example, Green, Malpezzi and Mayo (2005) show that when demand falls, the market cannot easily reduce the quantity of housing available because housing is durable. This asymmetric nature of housing makes the supply curve especially downwardly inelastic. Zoning restrictions and geographic constraints such as the fixed supply of land can also make the supply curve upwardly inelastic, though this varies substantially across the country (Saiz, 2010)

[14] Home values are forward looking in that they reflect both current demand and future expected demand for a property. Thus, the 15-point gap suggests that a large portion of the divergence in price change will persist. To check whether out findings are specific to the Covid-19 pandemic relative to past macroeconomic shocks, we reproduce the main home values figure for both Great Recession and 9/11 in Appendix A4. Both shocks do not produce divergence between regions showing the uniqueness of the Covid shock.

[15] Defined as $dX_t=(X_t-X_{t-1})/(0.5\times X_t+0.5\times X_{t-1})$

story for rent growth changes, are broadly in line with other research and popular narratives around the impact of Covid on real estate.[16]

In columns (5) to (8) of Table 1, we show the results of the same set of regressions as columns (1) to (4) except with the percent change in home value index as the dependent variable. Interestingly, the WFH coefficient switches signs. One possible explanation for this is that WFH affects the demand for housing on two margins. On the extensive margin, WFH may enable residents to leave a zip code reducing the total number of residents. On the intensive margin, WFH may increase the demand for housing space perhaps due to an increased need for home office space or industry variations. The distance to CBD coefficient is positive and significant indicating relative price appreciation in zip codes further away from the city center. In general, results are consistent with the donut effect: the rise of WFH has made dense areas near city centers less attractive relative to the suburbs.

3.2 The donut effect exists in migration flows for people and businesses

Figure 2 panel A uses USPS change-of-address data to show the now-familiar story of populations reallocating from CBDs to less dense zip codes within the largest metros in the US.[17] The outflows from CBDs are especially striking. Monthly population outflows (Figure 2a) increase to almost 2% of the pre-Covid population for the CBDs of the 12 largest US metros. In fact, since March 2020, the net population outflows versus their pre-pandemic trend for the top 12 metro CBDs has cumulated to 15% (see Figure A6).[18] These values highlight that the pandemic-induced population flows are quantitatively material in terms of overall city-center density.

Panel B of Figure 2 shows monthly net business establishment inflows based on change-of-address requests as a share of the pre-Covid establishment stock. Business flows are broadly similar to those of population flows but have a much sharper initial drop. Business outflows from the top 12 CBDs versus pre-pandemic trends from Feb 2020 to Feb 2021 cumulate to around 14% of stock (Figure A6).

There are several possible explanations for the outflow of businesses. First, certain businesses like restaurants may be following the reallocation of people because this may also shift consumption spending on services. Businesses may also have gained flexibility on their location due to the reduction in commutes for employees under WFH. Studying these dynamics in more depth requires microdata on business establishments and is a subject for future work.

[16] We tried including total Covid deaths per capita since the start of the pandemic as a control and find broadly similar results.
[17] As a basic data check, Appendix A3 confirms a positive relationship between net population flows and residential rental and price growth for zip codes in the 12 largest US metros.
[18] To adjust for the pre-pandemic trend, we take the difference in monthly flow with the flow level in Feb 2020 before cumulating. An alternative measure of the impact of the pandemic is to simply look at the total change in population and businesses as a share of their stock since February 2020 in the CBD (without any adjustment for pre-trends). Using this alternative approach we find that the reduction in population is 19% and the reduction in businesses addresses is 14%. The slightly larger population outflows using this approach highlight that there were already small pre-existing population outflows from CBDs before the pandemic.

Figure 3 displays heat maps of the cumulative net population inflow from Feb 2020 to Feb 2021 as a percent of pre-Covid population for the New York metro area (Panel A) and the San Francisco Bay Area metro area (Panel B). The heat maps show a striking pattern of outflows from the dense central city areas of lower Manhattan (in New York) and San Francisco and Oakland (in the Bay Area) towards the suburbs. Maps for other example cities, Boston and Los Angeles, in Appendix A7 reveal similar flows of population out from city centers to suburban areas.

To investigate the factors driving population flows, we run regressions of a similar specification to Equation 1 (which examined real-estate prices) except with cumulative net flows as a percent of stock from Feb 2020 to Feb 2021 as the dependent variable:

$$\%\,\Delta pop_{i,t} = \alpha + \beta_1\,\%\Delta\,pop_{i,t-1} + \beta_2 \ln density_i + \beta_3 \ln dist\_CBD_i + \psi_m + \epsilon_i \qquad (2)$$

As we see in Table 2 columns (1) to (4) that net flows are strongly related to distance to the CBD, density and WFH exposure.

Table 2 columns (5) to (8) shows the results of similar regressions for cumulative net inflows of business establishments as a percent of total stock as the dependent variable. The regressions broadly confirm the donut effect pattern: density and WFH share have negative coefficients and distance to CBD has a positive coefficient.

3.3 Heterogeneity across cities

How does the donut effect vary across cities? Figure 4 examines the donut effect in metros outside the top 12 metros, finding little residential price growth dispersion. There is some evidence that CBDs see slower price appreciation in cities ranked 13 to 50, but nothing in the remaining cities ranked 51 to 365 by size. Figure 5 shows heterogeneity in the donut effect across metros as measured by population flows, revealing a similar result. A clear drop in population flows in the CBDs of the largest 12 US cities, a milder drop in cities sized 13 to 50, and no impact in cities 51 to 365.[19] We see in Figure A1 in the appendix a similar result for rents – a strong donut effect in the largest 12 cities, a milder effect in cities sized 13 to 50, and little impact in the remaining cities ranked 51 to 365.

What explains variation in the donut effect across cities? As seen in the previous results, zip-codes with a greater WFH share take bigger hits so if larger metros have greater WFH shares in their city centers then we should expect such cities to have larger donut effects. Indeed, Althoff, Eckert, Ganapati, and Walsh (2020) show that America's largest cities have the highest concentration of skilled service workers in industries like tech and finance who can WFH. Furthermore, the incentive to relocate one's home when given the option to work-from-home may be greater in higher-priced locations which also tend to have greater population density.

These findings can be rationalized by thinking of WFH as a technology that mitigates traditional agglomeration forces. Such forces have driven skilled workers to cluster near city centers pushing up population density and price levels (see e.g. Glaeser and Gottlieb (2009) and

[19] There is also evidence of CBD seasonality in the data, with populations falling in the summer.

Diamond (2016)). Thus, cities with a greater share of residents who can WFH and high population density which contributes to higher housing prices are more vulnerable to changes from Covid-induced WFH.

3.4 Within-metro vs between-metro reallocation of economic activity

Several recent news articles have hypothesized a flight from large cities like New York and San Francisco to smaller areas like Tulsa, Oklahoma or Nashville, Tennessee. In this section, we test this hypothesis by examining the relationship between metro-level population density and both home price changes and migration patterns post-Covid. A key feature of our analysis is to compare the *within*-metro relationship between population density and housing prices or migration flows with the *between*-metro relationship.

Figure 6 shows three zip code-level binscatters of the percent change in home value index (Panel A), population (Panel B), and business establishment stock (Panel C) plotted against population density after controlling for the pre-Covid trend. We include MSA fixed effects to show the *within*-metro relationships. Similar to Sections 3.1 and 3.2, the three plots show a clear reallocation of real estate demand, people, and business establishments away from high density zip codes and CBDs towards lower density zip codes further from the city center.

Figure 7 plots the same three figures as Figure 6, except at the metro-level instead of the zip code level. The figures are on the same y-scale and have the same controls, except Figure 7 has metro-fixed effects. Thus, Figure 7 examines changes *between* metros rather than *within* metros. All three regression lines show flatter slopes compared to the within-metro binscatters. In fact, the metro-level home price plot shows a positive relationship between home price changes and metro-level population density. The flatter slopes indicate that the *within*-metro reallocation of economic activity is stronger than the *between*-metro reallocation. Furthermore, the positive relationship between density and home price changes at the metro-level suggests that real estate market expect denser metros to perform well in the longer-term.

There are several interpretations of this data. First, many of the cross-city moves during the pandemic may prove to be temporary. As cities reopen, residents may move back to their pre-Covid metro areas, though perhaps slightly further away from the city center than their previous residences.

A second explanation is that large dense metros typically have a high share of workers in industries like tech and finance, which have grown as a share of GDP during Covid. Thus, some of the price growth in previously expensive metros may be due to an income effect. For example, Covid has induced a reallocation of economic activity towards the software industry (Barrero, Bloom, and Davis, 2020b), which may have disproportionately benefited the incomes of both previous and new residents of the suburbs of technology-heavy cities like San Francisco and New York.

Third, the individuals who are moving to large metro suburbs may be spending a greater share of income on housing (and are wealthier). Since large metros have seen more city-to-suburb movement than small metros, the increased spending on housing for these newly suburban dwellers could explain the metro-level price growth. Large metros also tend to have a greater share of residents who can WFH, and Stanton and Tiwari (2021) find that home workers spend a greater share of income on housing then non-homeworkers. Thus, the increase in WFH in large metros could also contribute to metro-level price growth. Our view is that all three explanations may be at play and estimating their relative magnitudes is a subject for future research.

4 Model

In this section, we describe the basic features of a simple spatial equilibrium model in order to rationalize the key findings of the empirical section. The model is loosely inspired by the one-city two-location model proposed by Liu and Su (2020) but with the following key differences. First, we add two more locations in order to model the between vs within dynamics documented in the data. Second, we add in productivity and wage differences to differentiate between the two metros and modify the functional forms of the utility function and housing supply curves. Finally, we simulate both a hybrid-WFH shock and a full-time WFH shock. Overall, the purpose of this model is to illustrate how both the within-metro and between-metro population flow dynamics change under very simple assumptions on the nature of WFH.

4.1 Model setup

Consider two metro areas, one large and one small. Each metro has a city center and a suburb giving a total of four locations. Locations are indexed as follows: big metro city center = 1, big metro suburb = 2, small metro city center = 3, small metro suburb = 4. Homogeneous individuals choose a location to maximize utility, which is a function of wages, amenities, commute costs, and housing rents.

Utility is Cobb-Douglas in wages, commute costs, amenities, and rents.

$$u_i = w_i^{\beta} c_i^{-\theta} a_i^{\gamma} r_i^{-\beta} \tag{3}$$

We let productivity and amenities vary by location. Rents have a constant elasticity with respect to population level. In Appendix B1, we describe the model ingredients in more detail. We also solve for the spatial equilibrium under three scenarios: (i) no WFH, (ii) hybrid WFH, and (iii) full-time WFH.

4.2 Commute costs

We simulate three states of the world based on the level of their commute costs shown in the table below.

Average commute costs				
	Large metro		Small metro	
	City center	Suburb	City Center	Suburb
No WFH	1	x	1	x
Hybrid WFH	π	πx	π	πx
Full-time WFH	0	0	0	0

Here, $x > 1$ represents the cost of commuting from suburb to city relative to a baseline cost of 1 for within-city commuting. $1 - \pi$ represents the share of days worked from home in the hybrid setting. Therefore, we multiply commute costs by π to obtain the new commute cost under hybrid WFH. Survey data from Barrero, Bloom and Davis (2020) indicates that employees who will WFH post pandemic (about half of all employees) will spend 2 days a week at home post-pandemic, implying $\pi \approx 0.6$.

4.3 Comparative statics

To solve for the spatial equilibrium, we equate log utility across our four locations since we have homogenous individuals. We derive solutions for the difference in population both between each city center and its corresponding suburb as well as between the two metro regions in Appendix B1.

In both hybrid and full-time WFH, there is reallocation from city centers to their respective suburbs, though the degree of reallocation under hybrid WFH is less than that of full-time WFH. The parameter π, which is the share of days worked in the office, governs the extent of the reallocation under hybrid-WFH. A smaller value of π, or more remote work, leads to more reallocation.

Furthermore, the relative metro-level populations are pinned down solely by productivity and amenities which do not change with partial telework. Therefore, though there is positive *between*-metro reallocation with full-time WFH proportional to underlying productivity differences, there is no *between*-metro reallocation under hybrid WFH. In general, hybrid WFH generates qualitative predictions that better match the patterns seen in the USPS and Zillow home values data than does full WFH.

5 Conclusion

Covid-19 has induced substantial change to the organization of work and economic activity. In this paper, we characterize how these shifts have impacted migration patterns and real estate markets both within and across US cities.

This paper contributes several findings to the growing literature on Covid-19, working-from-home, migration, and real estate markets. First, we establish evidence supporting a "donut effect" in migration patterns and real estate markets. About 15% of population and business establishments appear to have moved out of the centers of large cities over the first year of the pandemic. Much of this movement has been to the suburbs which have seen a price growth divergence from their city centers of almost 15 percentage points.

Our second contribution is identifying heterogeneities in how migration patterns and real estate markets have responded across almost the full set of US metros. There is clear evidence of a donut effect in the 12 largest US cities, some evidence in the next 13 to 50 sized US cities, and no evidence in smaller cities beyond this. This pattern suggests that the largest US cities have seen the sharpest movement of economic activity out of city centers into the surrounding suburbs.

Our third contribution is showing that the *within*-metro reallocation of economic activity, i.e. the donut effect, is stronger than the *between*-metro reallocation of activity from dense metros to less dense metros. To interpret this finding, we build a simple spatial equilibrium model with two metro areas, each with a city center and a suburb. Our model generates qualitative patterns that better match the empirical data under the hybrid-WFH scenario compared to the full-time WFH scenario. We take this as evidence that post-pandemic, work will be primarily hybrid, with workers commuting to their business premises a couple days a week. This is less than pre-pandemic, making suburbs relatively more popular, but too frequent to allow employees to leave the cities containing their employer.

This paper raises several questions for future research. First, as hypothesized previously, future work should directly measure whether individuals who have left city centers are spending more on housing. This fact could help explain the booming real estate markets in large metros. Second, the donut effect may lead to persistent reductions in tax revenues for major cities due to the outflow of people, businesses, and economic activity. Since WFH is highly correlated with high-wage workers, the reallocation of high-wage workers from city centers is likely to make the drop in consumption spending on services especially large. Modeling the size of this impact in the longer-term is important for city governments contending with the reduction in revenues.

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Appendix B1: Model
In this Appendix, we detail the ingredients of our model and walk through its solution.

B1.1 Productivity & Wages
We assume two levels of productivity, w_l and w_s, for the large and small metro respectively, where $w_l > w_s$. In this simplified setting with perfectly competitive labor markets, workers earn their marginal product so wages equal productivity. An example for such metros is New York and Indianapolis, respectively. We take productivity to be exogenous to abstract away from the underlying drivers of productivity. One limitation of this approach is that productivity responds endogenously to population density as documented by Glaeser and Gottlieb (2009) and Ciccone and Hall (1996). Because we are interested in qualitative predictions though, this assumption is justified since agglomeration will only strengthen the relationships found in the model. We further assume that productivity does not change when a worker is remote compared to non-remote. This assumption is uncertain but has some empirical basis – recent evidence indicates remote workers may even see a productivity boost (Barrero, Bloom, and Davis, 2021).

B1.2 Amenities
We define amenity levels across the four locations as follows:
- large metro city center = a_1
- large metro suburb = a_2
- small metro city center = a_3
- small metro suburb = a_4

We let $a_1 > a_2$ and $a_3 > a_4$. Alternate permutations of the amenity levels are useful to consider because many individuals value traditional suburban amenities like parks, neighborhood safety, and school quality over traditional city amenities like restaurants, bars, and tourist attractions.

B1.3 Rents
The final feature of the model is housing rents. We let rental costs have a constant elasticity with respect to population:

$$\log r_i = \alpha + \epsilon_i \log n_i \tag{4}$$

In reality, the functional form for this relationship depends on location-specific factors such as zoning, but we abstract away from this heterogeneity for analytical convenience.

B1.4 Spatial Equilibrium
We use the following clearing condition to derive the spatial equilibrium. Since agents are homogeneous, log utility will be equal across locations i.e. $u_i = u_j$ for all i, j. We use this condition to calculate the percent differences in population between areas under each WFH scenario.

B1.4.1 No work-from-home
The log utility levels for each of the four locations are given by:
- Large city: $u_1 = \beta w_1 - \theta + \gamma a_1 - \beta(\alpha + \epsilon n_1)$
- Large suburb: $u_2 = \beta w_1 - \theta x + \gamma a_2 - \beta(\alpha + \epsilon n_2)$
- Small city: $u_3 = \beta w_2 - \theta + \gamma a_3 - \beta(\alpha + \epsilon n_3)$
- Small suburb: $u_4 = \beta w_2 - \theta x + \gamma a_4 - \beta(\alpha + \epsilon n_4)$

Equating the log utilities pairwise yields the following equilibrium percent differences in population since we are operating in log space:
- $n_1 - n_2 = \frac{\theta(x-1)+\gamma(a_1-a_2)}{\beta\epsilon}$
- $n_3 - n_4 = \frac{\theta(x-1)+\gamma(a_3-a_4)}{\beta\epsilon}$

- $n_1 - n_3 = \frac{\beta(w_1 - w_2) + \gamma(a_1 - a_3)}{\beta\epsilon}$
- $n_2 - n_4 = \frac{\beta(w_1 - w_2) + \gamma(a_2 - a_4)}{\beta\epsilon}$

Observe that the *within*-metro difference (between city center and suburb) is pinned down by the commute cost term *x* and the relative amenity levels. Larger commute costs for the suburb drives more people to the city center. Furthermore, the *between*-metro difference (between the large metro and the small metro) is positively related to productivity differences and amenity differences. Larger productivity differences or amenity differences increase the total population in the larger metro area.

B1.4.2 Full work-from-home

Next, we consider the case of full-time work-from-home where commute costs go to zero in all locations. Note that no other parameters change in the model. With no commute costs, the only factor preventing full agglomeration on the large metro city center (which has the highest productivity and amenity levels) is housing rents.

The new log utility levels for each of the four locations are given by:

- Large city: $\bar{u}_1 = \beta w_1 + \gamma a_1 - \beta(\alpha + \epsilon n_1)$
- Large suburb: $\bar{u}_2 = \beta w_1 + \gamma a_2 - \beta(\alpha + \epsilon n_2)$
- Small city:$\bar{u}_3 = \beta w_2 + \gamma a_3 - \beta(\alpha + \epsilon n_3)$
- Small suburb: $\bar{u}_4 = \beta w_2 + \gamma a_4 - \beta(\alpha + \epsilon n_4)$

Equating the log utilities pairwise yields the following equilibrium percent differences in population since we are operating in log space:

- $n_1 - n_2 = \frac{\gamma(a_1 - a_3)}{\beta\epsilon}$
- $n_3 - n_4 = \frac{\gamma(a_3 - a_4)}{\beta\epsilon}$
- $n_1 - n_3 = \frac{\gamma(a_1 - a_3)}{\beta\epsilon}$
- $n_2 - n_4 = \frac{\gamma(a_2 - a_4)}{\beta\epsilon}$

Observe that the equilibrium population ratios are now solely pinned down by the relative amenities between locations. This makes sense as full-time WFH allows one to access the productivity level of the large metro, w_l, from anywhere. We can now consider differences between the no work-from-home setting and the full-work-from-home setting. There are two differences to consider. First, the *within*-metro population ratios no longer have a commute cost term so the difference in population ratios falls. Since rents are purely a function of population, the difference in rents also narrows. Third, the *between*-metro population ratios no longer have a productivity term so the difference in population between the large metro and small metro falls. All that remains are differences from amenities. Importantly, the model takes amenities as exogenous. But as Diamond (2016) shows, amenities respond endogenously to economic agglomeration so in a less simplified WFH model, population differences from amenities may fall further.[20]

B1.4.3 Hybrid work-from-home

Hybrid work-from-home is analytically similar to the baseline no work-from-home setting. The log utility level equations remain the same except the commute cost terms are now scaled down and are given by:

- Large city: $\tilde{u}_1 = \beta w_1 - \theta\pi + \gamma a_1 - \beta(\alpha + \epsilon n_1)$
- Large suburb: $\tilde{u}_2 = \beta w_1 - \theta x\pi + \gamma a_2 - \beta(\alpha + \epsilon n_2)$

[20] Such models assume consumption amenities like restaurants and nightlife respond endogenously to population. Natural amenities like access to water will remain generating some differences across locations in amenity levels. Empirical research confirms that such natural amenities lead to persistent effects on economic geography that are resistant to minor shocks like policies or natural disasters (Lee and Lin, 2018).

- Small city: $\tilde{u}_3 = \beta w_2 - \theta\pi + \gamma a_3 - \beta(\alpha + \epsilon n_3)$
- Small suburb: $\tilde{u}_4 = \beta w_2 - \theta x\pi + \gamma a_4 - \beta(\alpha + \epsilon n_4)$

Equating the log utilities pairwise yields the following equilibrium percent differences in population since we are operating in log space:

- $n_1 - n_2 = \frac{\theta\pi(x-1)+\gamma(a_1-a_3)}{\beta\epsilon}$
- $n_3 - n_4 = \frac{\theta\pi(x-1)+\gamma(a_3-a_4)}{\beta\epsilon}$
- $n_1 - n_3 = \frac{\beta(w_1-w_2)+\gamma(a_1-a_3)}{\beta\epsilon}$
- $n_2 - n_4 = \frac{\beta(w_1-w_2)+\gamma(a_2-a_4)}{\beta\epsilon}$

The equilibrium percent differences have the same form as the differences from the no WFH case. The sole difference is the commute costs term is multiplied by π in the *within*-metro percent differences. The model predicts that the population percent differences will decrease. This means the city center to suburb population difference will decrease for both metros in the hybrid WFH world. Interestingly, the *between*-metro population percent difference does not change because it does not depend on commute costs. Thus, the model predicts that though there is reallocation of population (and therefore real estate demand) *within* metro areas, there is zero reallocation *between* metro areas.

B1.5 Comparative statics

Combining the results from the previous equilibrium solutions, we derive the following comparative statics.

B1.5.1 Within metro reallocation

No telework vs full telework:

$$\Delta n_1 - n_2 + n_3 - n_4 = \frac{4\,\theta(x-1)}{\beta\epsilon} \quad \text{Commute costs}$$

$$+\frac{\gamma(a_1 - a_2 + a_3 - a_4)}{\beta\epsilon} \quad \text{Relative amenities}$$

$$-\frac{\gamma(a_1 - a_2 + a_3 - a_4)}{\beta\epsilon} \quad \text{Relative amenities}$$

$$= \frac{4\,\theta(x-1)}{\beta\epsilon} \quad \text{Reallocation} \tag{5}$$

Observe that there is a positive amount of within-metro reallocation as long as $x > 1$. Furthermore, recall that all variables are in log space so we interpret the reallocation term as a percent change in population from the city centers to the suburbs.

No telework vs partial telework:

$$\Delta n_1 - n_2 + n_3 - n_4 = \frac{4\,\theta(x-1)}{\beta\epsilon} \quad \text{Commute costs}$$

$$+\frac{\gamma(a_1 - a_2 + a_3 - a_4)}{\beta\epsilon} \quad \text{Relative amenities}$$

$$-\frac{4\theta\pi(x-1)}{\beta\epsilon} \quad \text{Relative commute costs}$$

$$-\frac{\gamma(a_1 - a_2 + a_3 - a_4)}{\beta\epsilon} \quad \text{Relative amenities}$$

$$= \frac{(1-\pi)4\,\theta(x-1)}{\beta\epsilon} \quad \text{Reallocation} \qquad (6)$$

Similar to the full telework case above, observe that there is positive within-metro reallocation as long as $x > 1$. Importantly, the extent of this reallocation is inversely proportional to the share of days that are worked in the office, π. Thus, when WFH increases, π decreases, leading to more reallocation. Comparing the two comparative statics, we see that within-metro reallocation is greater under full telework compared to partial telework. Equality is achieved when $\pi = 0$ or the share of days done at home is 1.

$$\Delta \text{ within-metro full WFH} = \frac{4\theta(x-1)}{\beta\epsilon} > \frac{(1-\pi)4\theta(x-1)}{\beta\epsilon} = \Delta \text{ within-metro hybrid WFH} \quad (7)$$

B1.5.2 Between metro reallocation

No telework vs full telework:

$$\Delta n_1 - n_2 + n_3 - n_4 = \frac{2(w_1 - w_2)}{\epsilon} \quad \text{Commute costs}$$

$$+\frac{\gamma(a_1 - a_2 + a_3 - a_4)}{\beta\epsilon} \quad \text{Relative amenities}$$

$$-\frac{\gamma(a_1 - a_2 + a_3 - a_4)}{\beta\epsilon} \quad \text{Relative amenities}$$

$$= \frac{2(w_1 - w_2)}{\epsilon} \quad \text{Reallocation} \qquad (8)$$

The relative metro-level populations with full telework no longer include the productivity term so there is sizable between-metro reallocation proportional to the productivity difference.

No telework vs partial telework:

$$\Delta n_1 - n_2 + n_3 - n_4 = \frac{2(w_1 - w_2)}{\epsilon} \quad \text{Commute costs}$$

$$+\frac{\gamma(a_1 - a_2 + a_3 - a_4)}{\beta\epsilon} \quad \text{Relative amenities}$$

$$-\frac{2(w_1 - w_2)}{\epsilon} \quad \text{Relative commute costs}$$

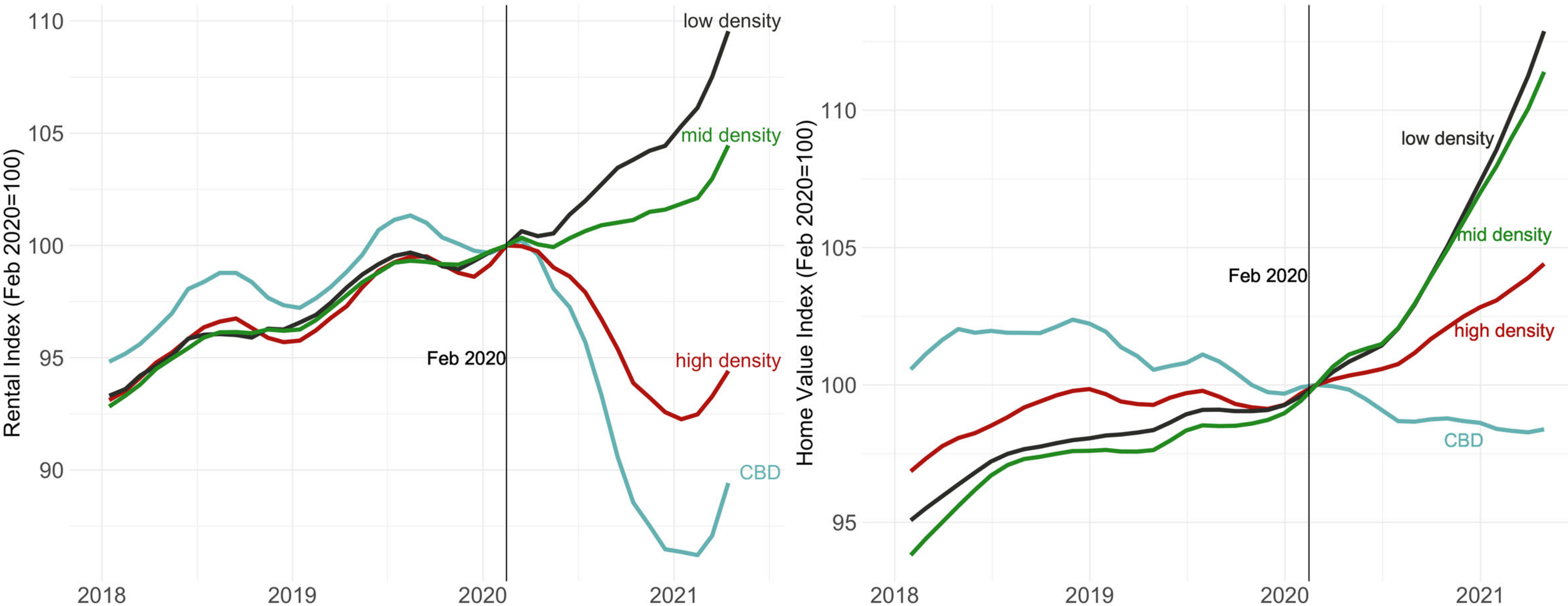
$$-\frac{\gamma(a_1 - a_2 + a_3 - a_4)}{\beta\epsilon} \quad \text{Relative amenities}$$

$$= 0 \quad \text{Reallocation} \qquad (9)$$

The relative metro-level populations are pinned down solely by productivity and amenities which do not change with partial telework. Therefore, there is no between-metro reallocation. Comparing the two comparative statics it is easy to see that there is a substantial amount of between-metro reallocation with full WFH proportional to underlying productivity differences, but there is no between-metro reallocation under hybrid WFH. In general, hybrid WFH generates qualitative predictions that better match the patterns seen in the USPS and Zillow home price index data than does full-time WFH.

Figure 1: The donut effect for the largest twelve US cities

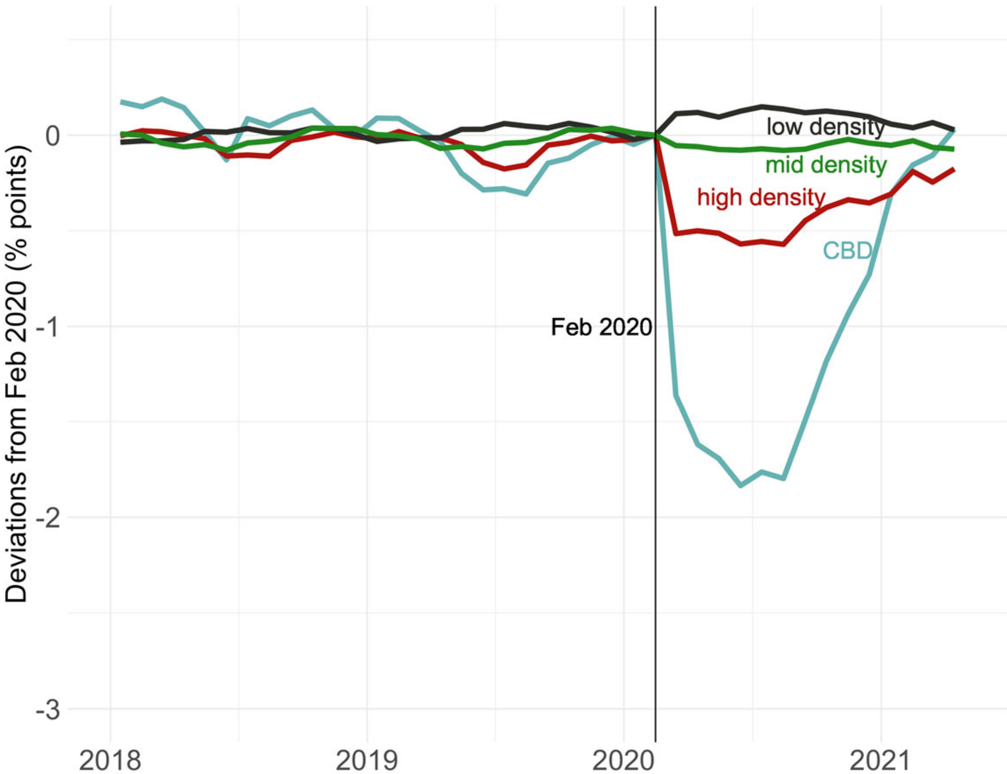
(a) Rental rates **(b) Home values**



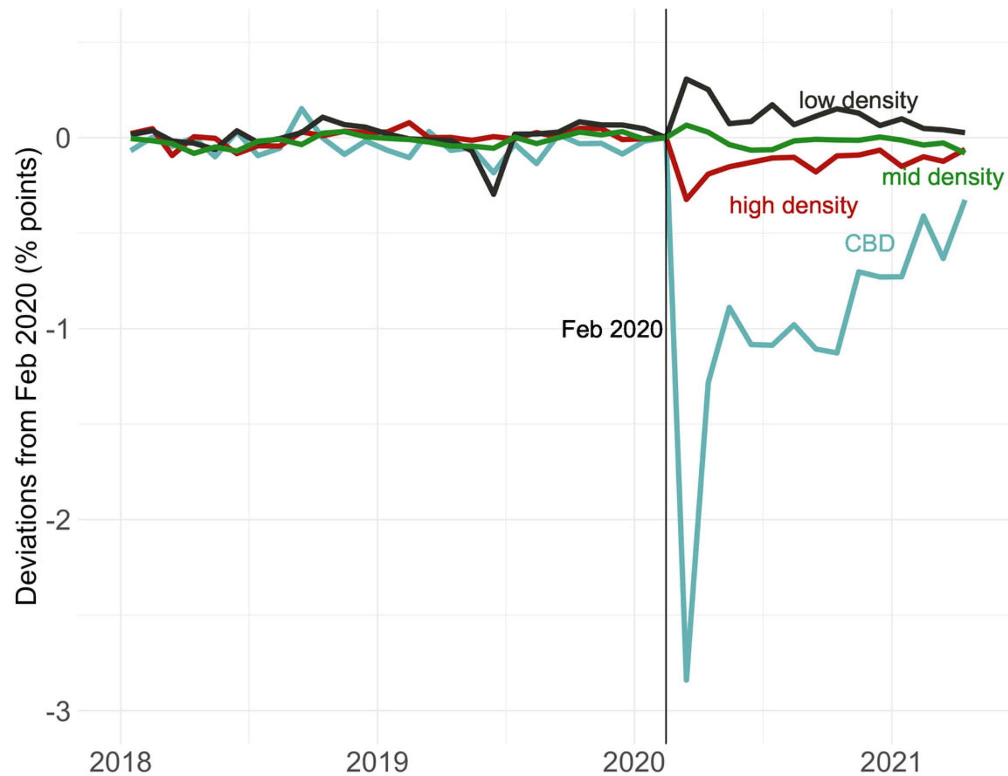
Notes: The figure shows Zillow's observed rental index (left) and home value index (right) in the 12 largest US metro areas (New York, Los Angeles, Chicago, Dallas, Houston, Miami, Philadelphia, Washington DC, Atlanta, Boston, San Francisco, and Phoenix – ordered by population). Zip codes are grouped by population density or presence in a Central Business District (CBD). A population weighted average is taken across all zipcodes in each bucket, and each aggregated index is normalized such that Feb 2020 = 100. Groups are given by high density = top 10%, mid density = 50-90th percentile, low density = 0-50th percentile and the CBD is defined by taking all zip codes with centroids contained within a 2 km radius of the CBD coordinates taken from Holian (2019). Population data taken from the 2015-19 5-yr ACS. Sources: Zillow, Census Bureau, Holian (2019). Data: Jan 2018 – Apr 2021.

Figure 2: Population and business flows follow the donut effect with sharp outflows from CBDs

(a) Monthly net population inflows as a percent of total

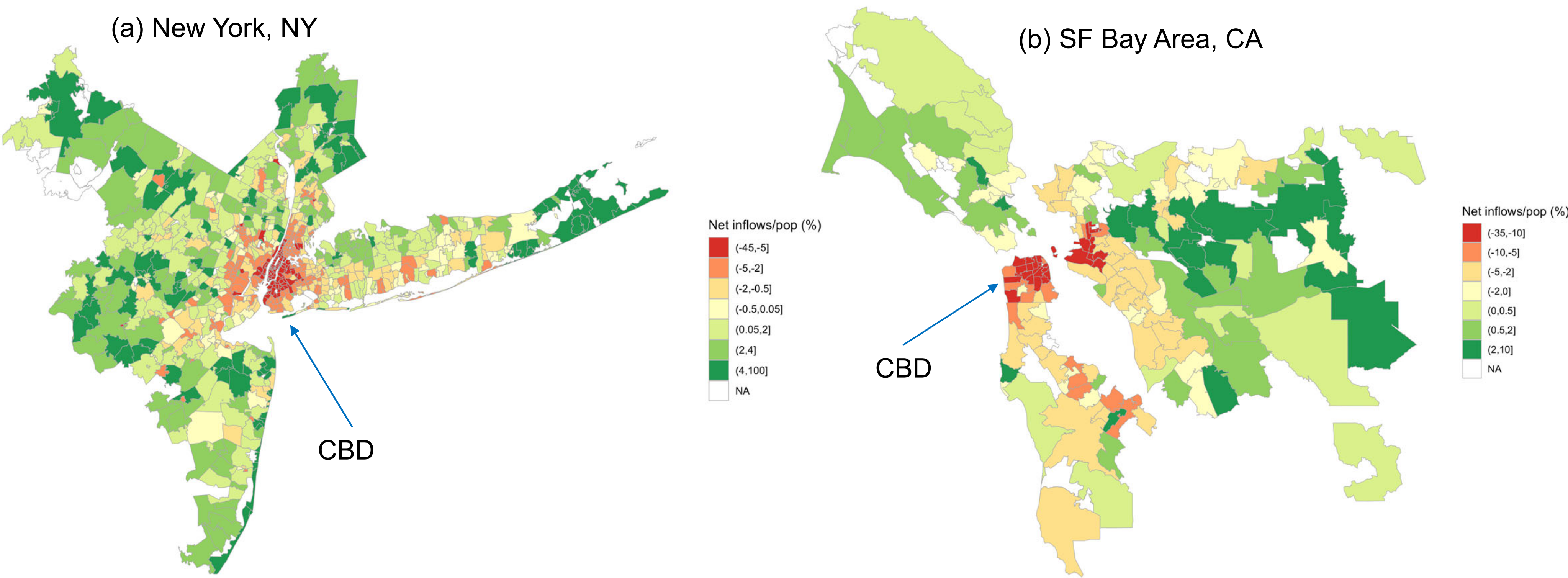


(b) Monthly net establishment inflows as a percent of total



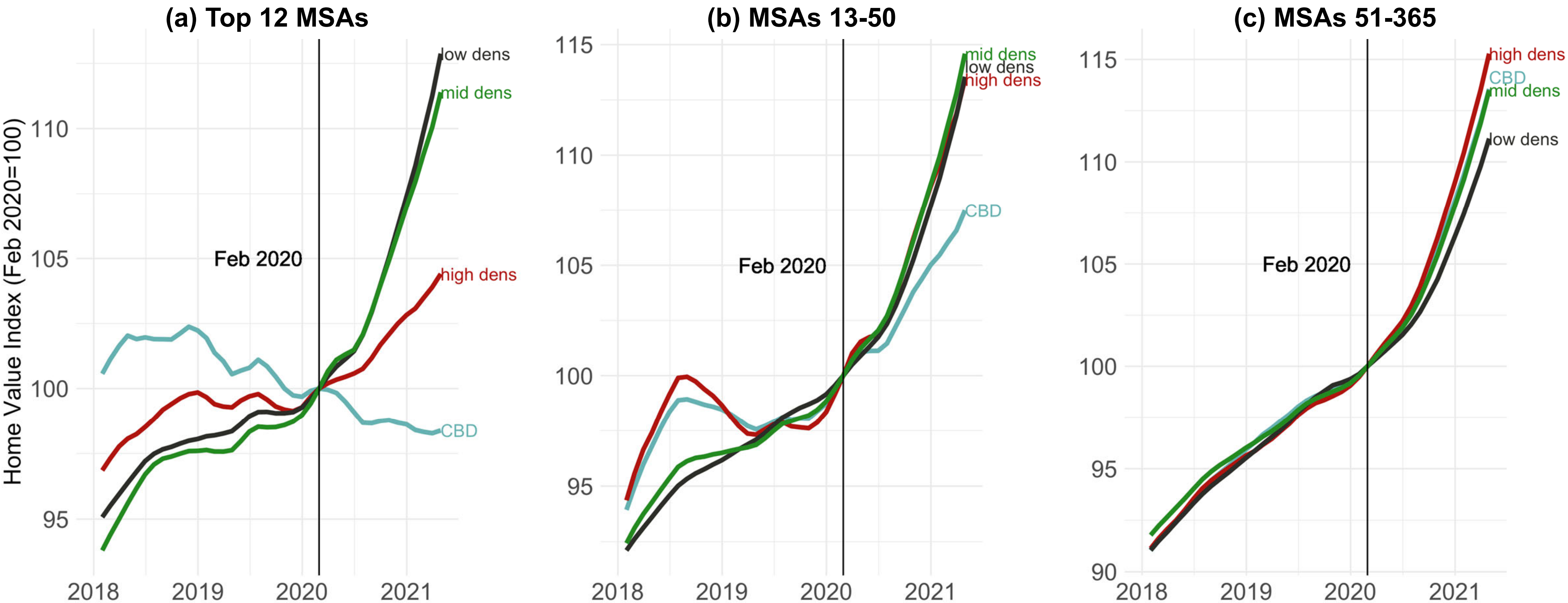
Notes: The left panel shows monthly net population inflows divided by 2019 population from the 2015-19 5-yr ACS. We multiply the number of household moves by the average household size from the Census Bureau, 2.5, and add the number of individual moves to calculate total population flows. The right panel shows monthly net establishment inflows divided by the 2018 establishment stock given by the 2018 Zipcode Business Patterns. Series are plotted as deviations from the Feb 2020 value. Zipcodes are grouped by population density or presence in a CBD. Flows are summed across all zip codes in a bucket before dividing by total population. Groups are given by high density = top 10%, mid density = 50-90th percentile, low density = 0-50th percentile. The Central Business District (CBD) is defined by taking all zipcodes with centroids contained within a 2 km radius of the CBD coordinates taken from Holian (2019). Sources: USPS, Census Bureau, Holian (2019). Data: Jan 2018 – Apr 2021.

Figure 3: Change of address flows occur from the city center to the suburbs



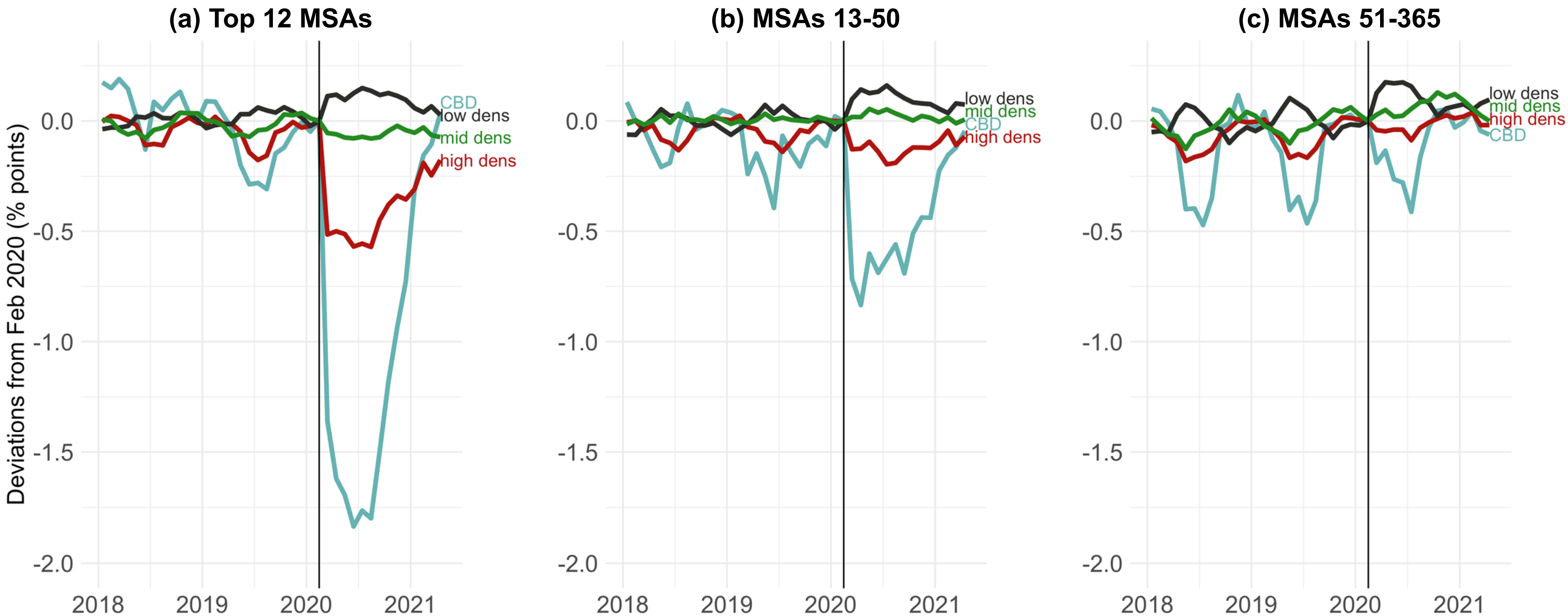
Notes: Both panels display heat maps of the cumulative net inflows (moves in – moves out) from Feb 2020-Feb 2021 as a percent of population (2015-19 5-yr ACS) at the zipcode level. The left panel shows the New York-Newark-Jersey City, NY-NJ-PA MSA and the right panel shows San Francisco-Oakland-Hayward MSA. Data on flows are calculated using USPS National change of address dataset. We multiply the number of household moves by the average household size from the Census Bureau, 2.5, and add the number of individual moves to calculate total population flows. Sources: USPS, Census Bureau.

Figure 4: The donut effect is strongest in the largest cities



Notes: The figure shows Zillow's home value index grouped by population density. Panel A pools the top 12 metros by population, panel B contains metros 13-50. and panel C gives the remaining metros (we have data on 365 in total). Zipcodes are grouped by population density or presence in a CBD. A population weighted average is taken across all zipcodes in each bucket, and each aggregated index is normalized such that Feb 2020 = 100. Density groups are given by high = top 10%, mid = 50-90th percentile, low = 0-50th percentile and populations are taken from the 2015-19 5-yr ACS. The Central Business District (CBD) is defined by taking all zipcodes with centroids contained within a 2 km radius of the CBD coordinates taken from Holian (2019). Sources: Zillow, Census Bureau, Holian (2019). Data: Jan 2018 - Apr 2021.

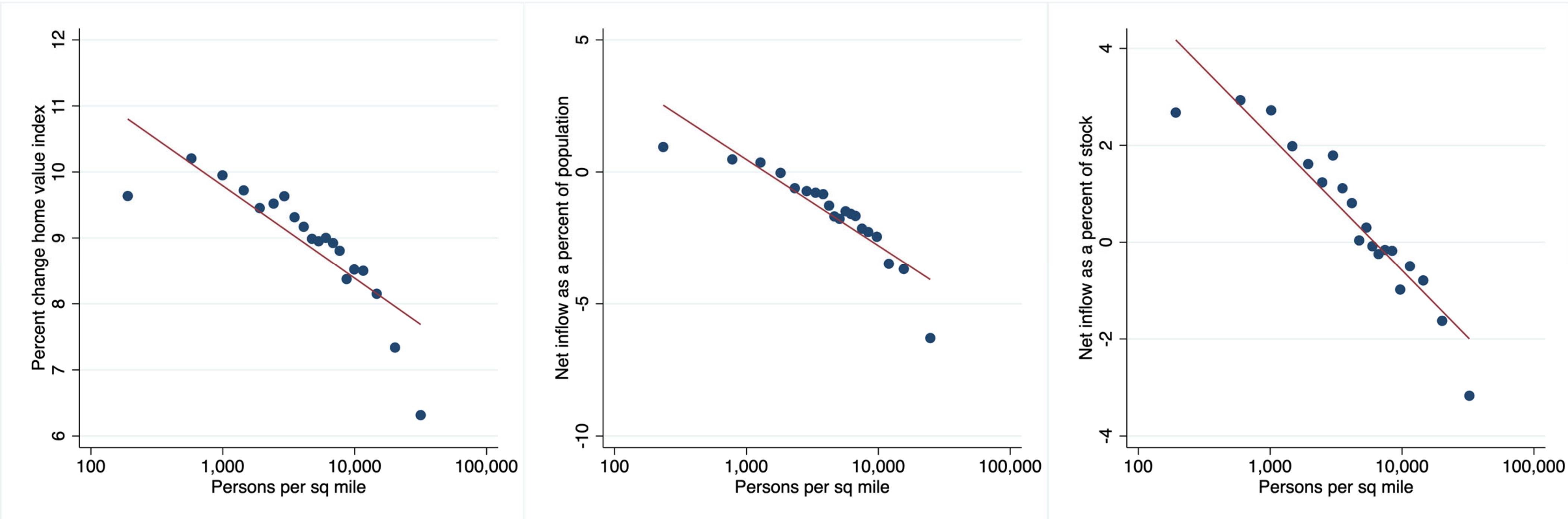
Figure 5: Donut effect is strongest in large cities for population flows



Notes All three panels shows monthly net population inflows divided by 2019 population from the 2015-19 5-yr ACS. Panel A pools the top 12 metros by population, panel B contains metros 13-50. and panel C gives the remaining metros (we have data on 365 in total). We multiply the number of household moves by the average household size from the Census Bureau, 2.5, and add the number of individual moves to calculate total population flows. Series are plotted as deviations from the Feb 2020 value. Zipcodes are grouped by population density or presence in a CBD. Flows are summed across all zip codes in a bucket before dividing by total population. Groups are given by high density = top 10%, mid density = 50-90th percentile, low density = 0-50th percentile. The Central Business District (CBD) is defined by taking all zipcodes with centroids contained within a 2 km radius of the CBD coordinates taken from Holian (2019). Sources: USPS, Census Bureau, Holian (2019). Data: Jan 2018 – Apr 2021.

Figure 6: The donut effect *within* metros for housing prices and change-of-address requests

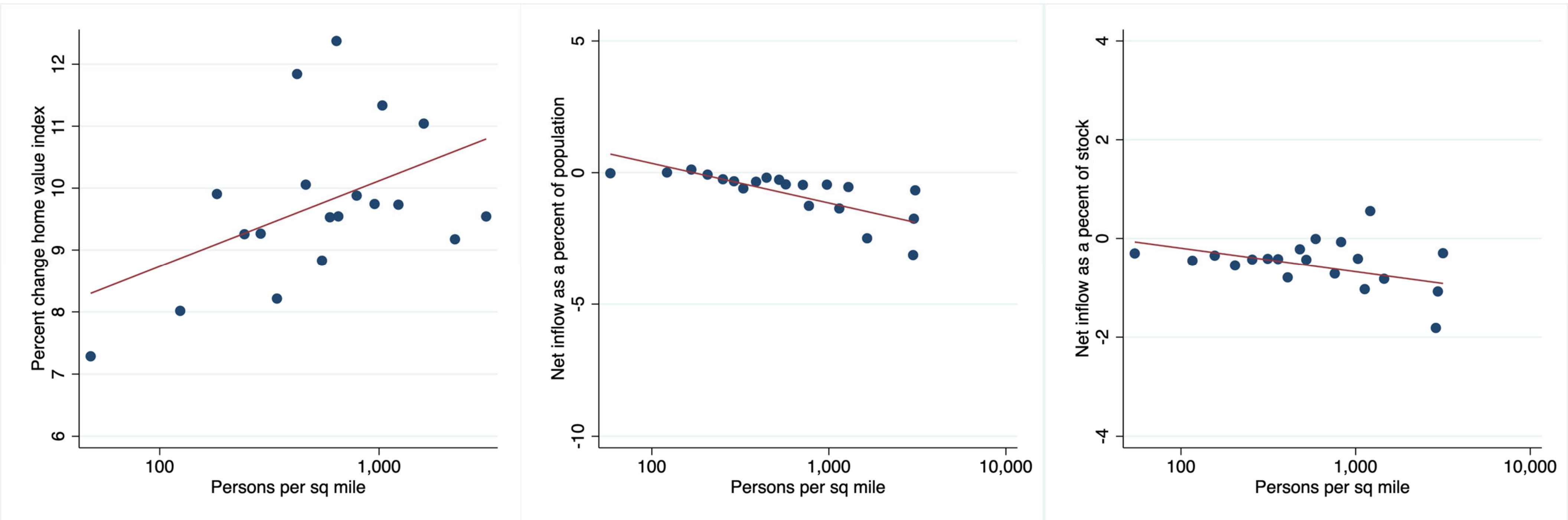
(a) Housing prices **(b) Population net inflows** **(c) Business net inflows**



Notes: Panel (a) shows a binscatter of the year over year percent change in the Zillow Home Value Index from Q1 2020-2021 against the log population density (persons/sq mile) controlling for MSA-fixed effects and the prior year's trend. Panels (b) and (c) show the same plot except with cumulative net population inflows as a percent of total population from the 2015-19 5-yr ACS and net business establishment inflows flows as a percent of establishment stock from the 2018 Zipcode Business Patterns. We multiply the number of household moves by the average household size from the Census Bureau, 2.5, and add the number of individual moves to calculate total population flows. Sources: USPS, Zillow, Census Bureau.

Figure 7: Prices are rising in large metros although population is moving in the opposite direction

(a) Housing prices **(b) Population net inflows** **(c) Business net inflows**



Notes: Panel (a) shows a binscatter of the year over year percent change in the MSA-level Zillow Home Value Index from Q1 2020-2021 against the MSA's log population density controlling for the prior year's trend. Panels (b) and (c) show the same plot except with cumulative net population inflows as a percent of total population from the 2015-19 5-yr ACS and net business establishment inflows flows as a percent of establishment stock from the 2018 Zipcode Business Patterns. We multiply the number of household moves by the average household size from the Census Bureau, 2.5, and add the number of individual moves to calculate total population flows. Sources: USPS, Zillow, Census Bureau.

Table 1: Density, distance from CBD and working from home explain the donut effect.

	Percent change in index Feb 2020 – Feb 2021							
	Rents (1) – (4)				Home values (5) – (8)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Density	-3.188***			-1.596***	-0.609***			-0.259***
	(0.162)			(0.042)	(0.071)			(0.044)
Dist to CBD		4.124***		2.211***		0.984*		0.708***
		(1.411)		(0.200)		(0.507)		(0.066)
Share of 2019 residents can WFH			-25.344***	-20.853***			0.272***	0.769**
			(0.182)	(0.244)			(0.058)	(0.364)
Observations	1,202	1,202	1,202	1,202	3,693	3,693	3,693	3,693
R^2	0.580	0.625	0.567	0.734	0.741	0.746	0.712	0.749

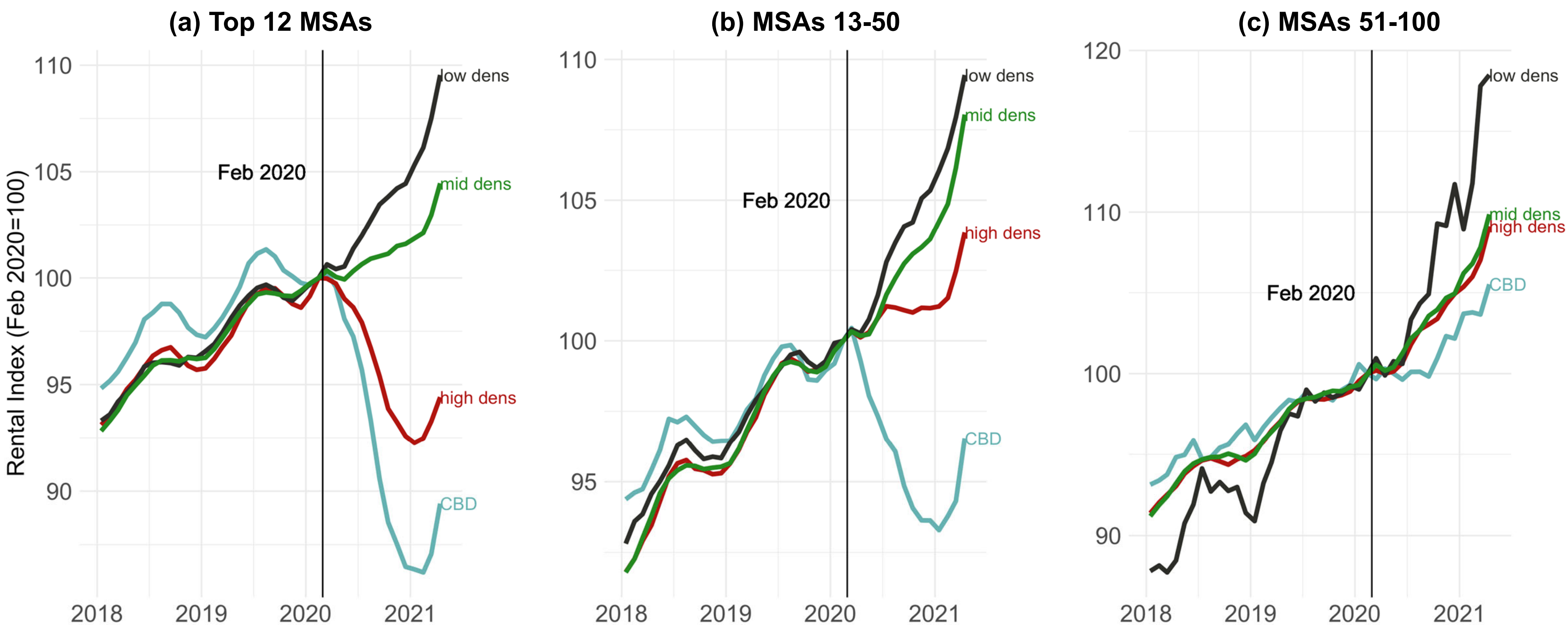
Notes: The table shows a set of population weighted regressions of the year over year percent change in Zillow's rental index or home value index from Feb 2020 to Feb 2021 regressed on population density, distance to CBD, and the share of residents who can WFH in 2019. Population estimates are the from the 2015-19 5-yr ACS. WFH shares are calculated by merging the industry distribution of residents from LODES and the share of jobs that can be done from home from Dingel and Neiman (2020) at the 2-digit NAICS level. We control for the percent change in the index over the previous year (Feb 2019 to Feb 2020). We limit our dataset to the top 12 US metros by population. All regressions include MSA fixed effects and robust standard errors. *p<.1, **p<.05, ***p<.01. Sources: Zillow, Census Bureau, Dingel and Neiman (2020).

Table 2: Density, distance from CBD and working from home explain the donut effect.

	Cumulative change in variable Feb 2020 – Feb 2021 as a percent of stock							
	Population (1) – (4)				Business establishments (5) – (8)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Density	-1.418***			-0.474***	-2.043***			-0.412***
	(0.263)			(0.100)	(0.168)			(0.124)
Dist to CBD		2.548**		1.914		3.004**		2.628***
		(1.169)		(1.193)		(1.287)		(0.150)
Share of 2019 residents can WFH			-9.019***	-6.720***			-9.725***	-0.938
			(0.212)	(1.196)			(0.153)	(0.888)
Observations	3,597	3,597	3,597	3,597	3,597	3,597	3,597	3,597
R^2	0.681	0.723	0.643	0.745	0.190	0.262	0.107	0.265

Notes: The table shows a set of population-weighted regressions where the dependent variables are cumulative net inflows from Feb 2020 to Feb 2021 as a percent of stock of either population or businesses. The population stock is taken from the 2015-2019 5-yr ACS and establishment stock from the 2018 Zipcode Business Patterns. We regress on population density, distance to CBD, and the share of residents who can WFH in 2019. Population estimates are the from the 2015-19 5-yr ACS. WFH shares are calculated by merging the industry distribution of residents from LODES and the share of jobs that can be done from home from Dingel and Neiman (2020) at the 2-digit NAICS level. We also control for the percent change in the index over the previous year (Feb 2019 to Feb 2020. We limit our dataset to the top 12 US metros by population. All regressions include MSA fixed effects and robust standard errors. *p<.1, **p<.05, ***p<.01. Sources: Zillow, Census Bureau, Dingel and Neiman (2020).

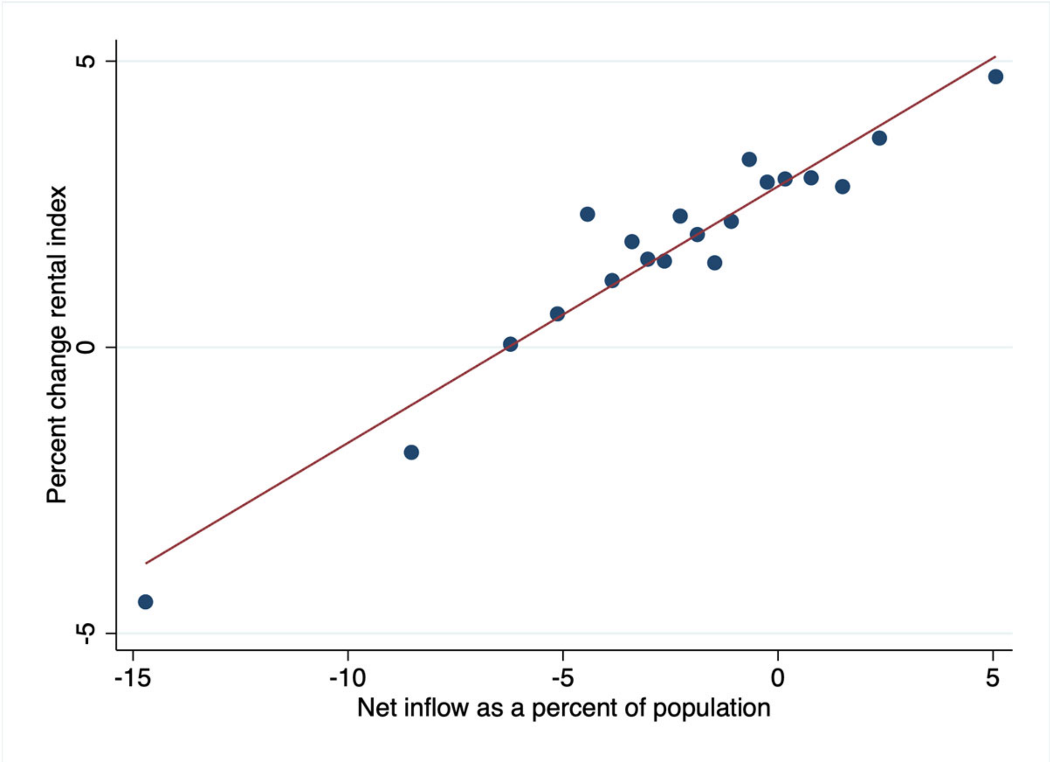
Appendix A1: Donut effect is largest in top 12 cities for rents



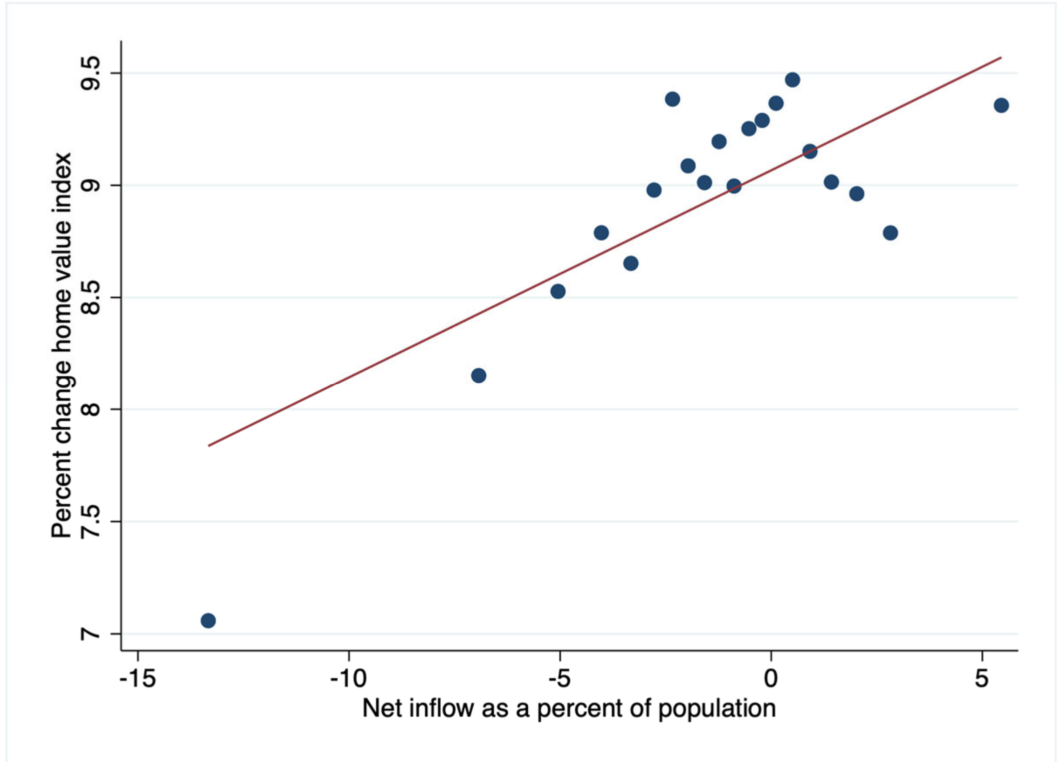
Notes: The figure shows Zillow's rental index grouped by population density. Panel A pools the top 12 metros by population, panel B contains metros 13-50. and panel C gives the remaining metros (we have data on 365 in total). Zipcodes are grouped by population density or presence in a CBD. A population weighted average is taken across all zipcodes in each bucket, and each aggregated index is normalized such that Feb 2020 = 100. Density groups are given by high = top 10%, mid = 50-90th percentile, low = 0-50th percentile and populations are taken from the 2015-19 5-yr ACS. The Central Business District (CBD) is defined by taking all zipcodes with centroids contained within a 2 km radius of the CBD coordinates taken from Holian (2019). Sources: Zillow, Census Bureau, Holian (2019). Data: Jan 2018 – Apr 2021.

Appendix A2: Net population inflows predict real estate rent and price growth

(a) Rental rates



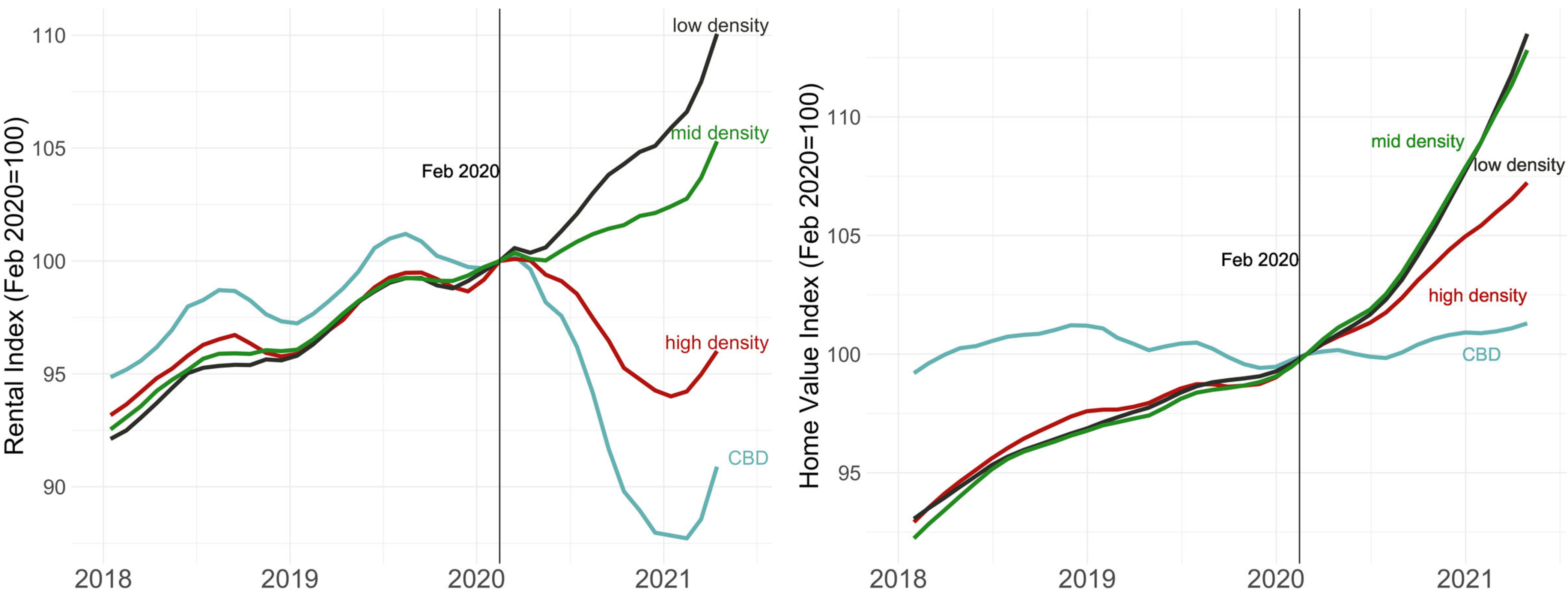
(b) Home values



Notes: Both charts show a binscatter of the year over year percent change in Zillow's rental index (a) or home value index (b) from Feb 2020 to Feb 2021 on the cumulative net population inflow as a percent of the 2015-2019 5-yr ACS population estimates at the zipcode level. We limit our dataset to the top 12 US metros by population. We control for population density (log), the pre-trend percent change in index from Feb 2019 – Feb 2020, and MSA-fixed effects. *p<.1, **p<.05, ***p<.01. Sources: USPS, Zillow, Census Bureau.

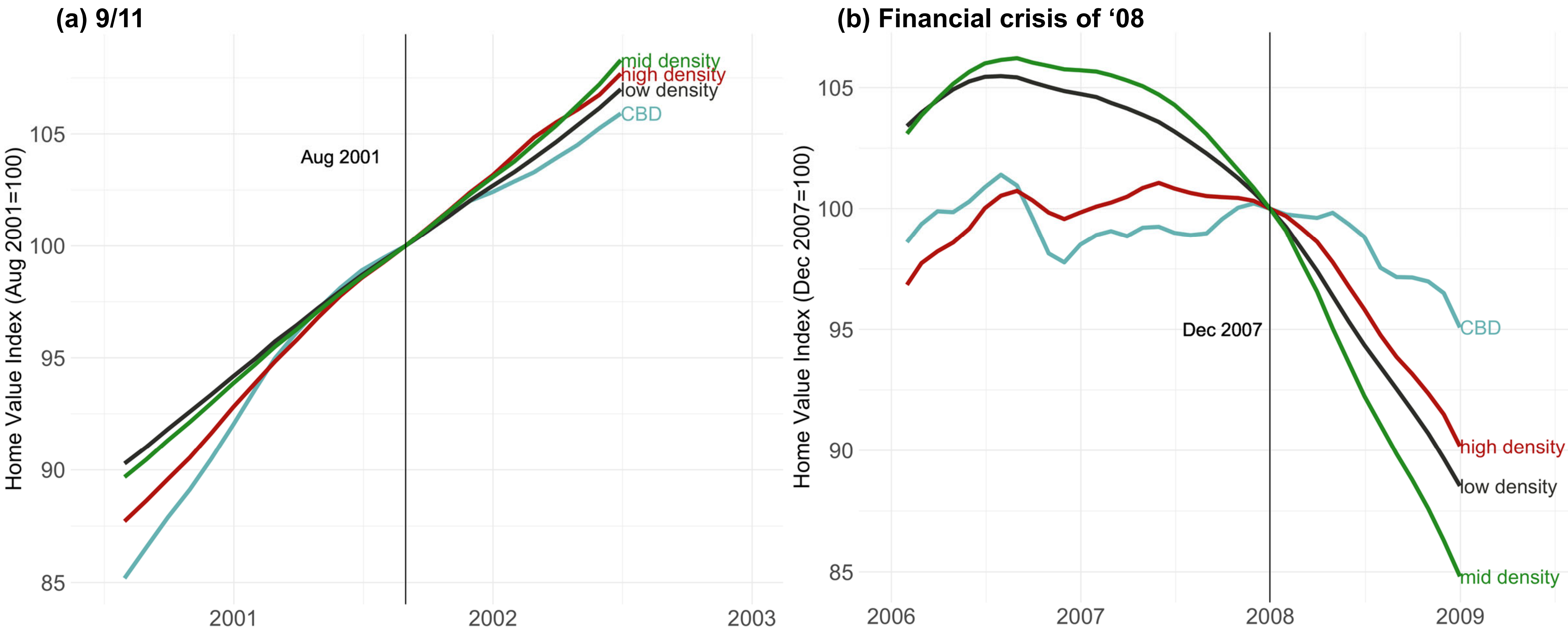
Appendix A3: The donut effect for the largest twelve US cities: equal weighting of all zipcodes

(a) Rental rates **(b) Home values**



Notes: The figure shows Zillow's observed rental index (left) and home value index (right) in the twelve largest US metro areas. Zipcodes are grouped by population density or presence in a CBD. Zipcode level series are first normalized to Feb 2020 = 100 and then a population-weighted average is taken across all zipcodes within a group (reversing the order of our standard approach such as in Figure 1). Groups are given by high = top 10%, mid = 50-90th percentile, low = 0-50th percentile. The CBD is defined by taking all zipcodes with centroids contained within a 2 km radius of the CBD coordinates taken from Holian (2019). Populations are given by 2015-19 5-yr ACS. Sources: Zillow, Census Bureau, Holian (2019). Data: Jan 2018 – Apr 2021.

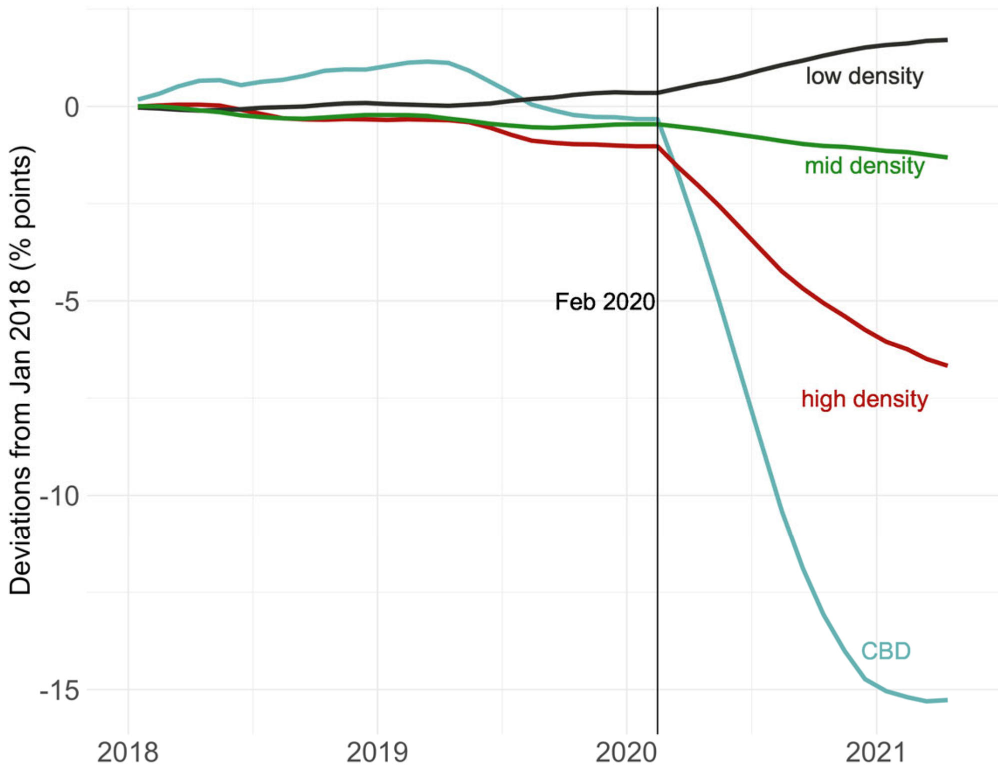
Appendix A4: Past macro shocks do not display the donut effect



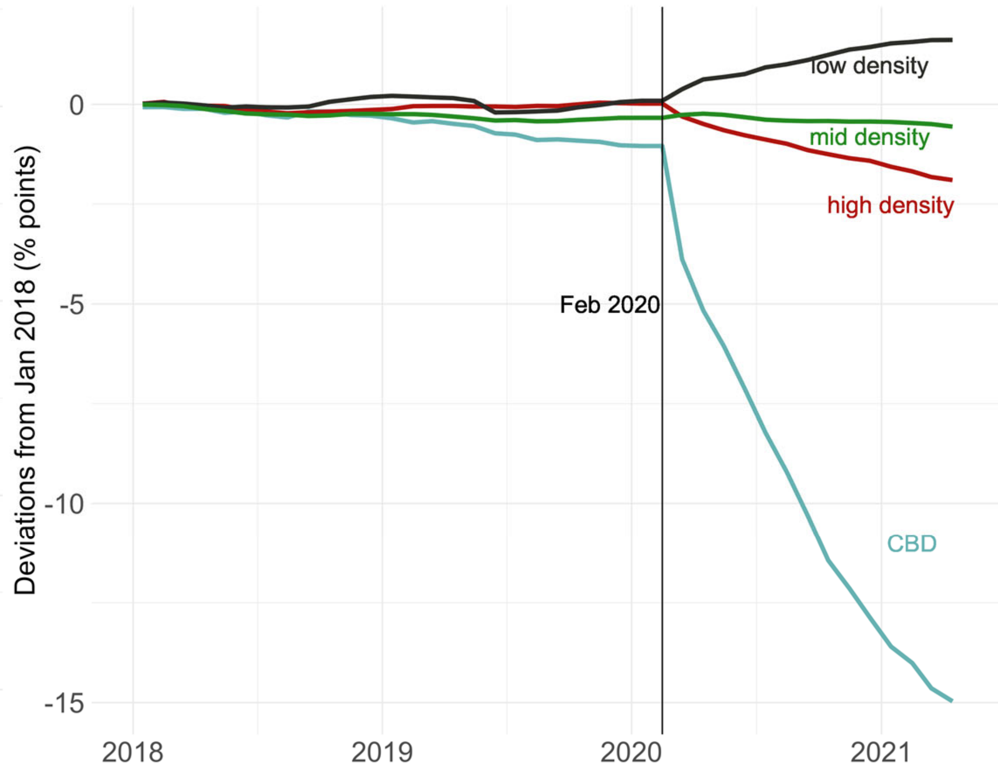
Notes: Both panels shows Zillow's smoothed home value index in the twelve largest US metro areas (the smoothed index was used because the raw index is not available before 2014). Zip codes are grouped by population density or presence in a CBD and a population-weighted average is taken across all zip codes within a group (using the 2010 Census population). Groups are given by high = top 10%, mid = 50-90th percentile, low = 0-50th percentile. Panel (a) is normalized such that Aug 2001 = 100 and panel (b) such that Dec 2007 = 100 to correspond to the 9/11 and Great Recession shocks respectively. The CBD is defined by taking all zip codes with centroids contained within a 2 km radius of the CBD coordinates taken from Holian (2019). Sources: Zillow, Census Bureau, Holian (2019). Data: (a) Jul 2000 – Jul 2002 (b) Jan 2006 – Jan 2009.

Appendix A5: Cumulative flows versus the pre-pandemic trend follow the donut effect with sharp outflows from CBDs

(a) Cumulative net population inflows as a percent of total

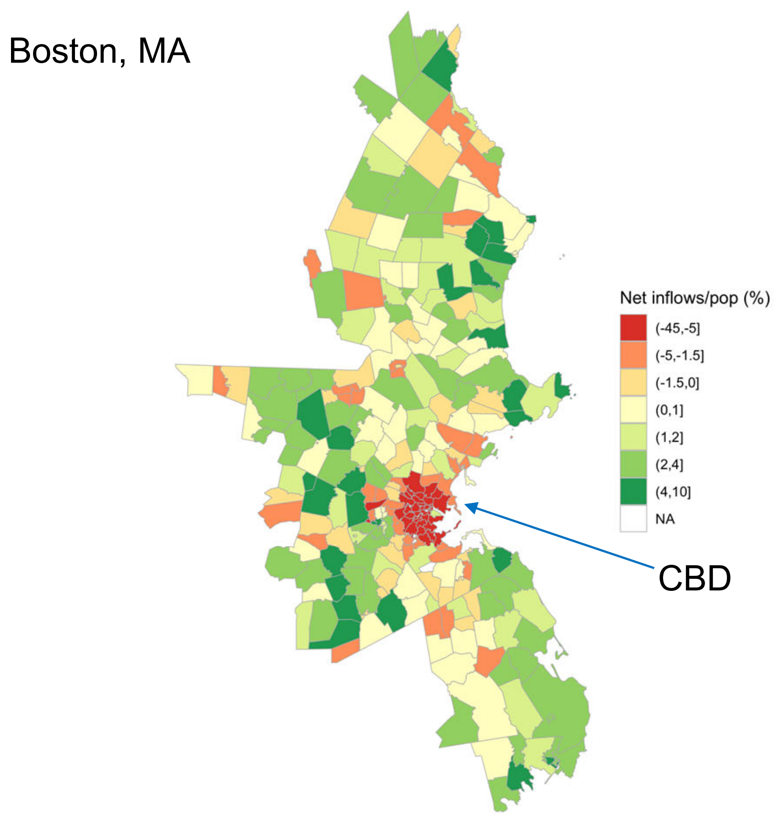


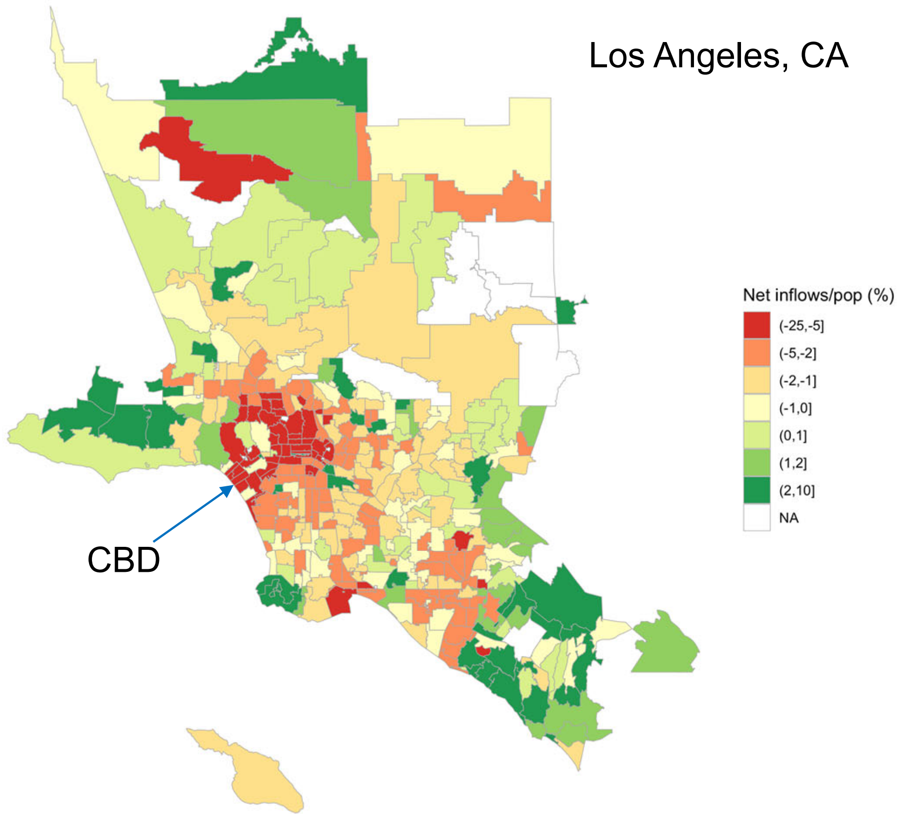
(b) Cumulative net establishment inflows as a percent of total



Notes: The left panel shows cumulative net population inflows divided by 2019 population from the 2015-19 5-yr ACS. We multiply the number of household moves by the average household size from the Census Bureau, 2.5, and add the number of individual moves to calculate total population flows. The right panel shows the cumulative net establishment inflows divided by the 2018 establishment stock given by the 2018 Zipcode Business Patterns. Both series are cumulated starting from Jan 2018 after differencing monthly inflows by their Feb 2020 value. This shows the cumulative flows above their pre-pandemic trend over this period. Zipcodes are grouped by population density or presence in a CBD. A population weighted average is taken across all zipcodes in each bucket. Groups are given by high density = top 10%, mid density = 50-90th percentile, low density = 0-50th percentile. The Central Business District (CBD) is defined by taking all zipcodes with centroids contained within a 2 km radius of the CBD coordinates taken from Holian (2019). Sources: USPS, Census Bureau, Holian (2019). Data: Jan 2018 – Apr 2021.

Appendix A6: Change of address flows occur from the city center to the suburbs





Notes: Both panels display heat maps of the cumulative net inflows (moves in – moves out) from Feb 2020-Feb 2021 as a percent of population (2015-19 5-yr ACS) at the zipcode level. The left panel shows the Boston-Cambridge-Newton, MA-NH MSA and the right panel shows Los Angeles-Long Beach-Anaheim, CA. Data on flows are calculated using USPS National change of address dataset. We multiply the number of household moves by the average household size from the Census Bureau, 2.5, and add the number of individual moves to calculate total population flows. Sources: USPS, Census Bureau.

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The Centre for Economic Performance Publications Unit
Tel: +44 (0)20 7955 7673 Email info@cep.lse.ac.uk
Website: http://cep.lse.ac.uk Twitter: @CEP_LSE