# The Donut Effect

## of Covid-19 on US (Global) Cities

2023 AEAs

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Ramani, Arjun and Nick Bloom. “The Donut Effect of Covid-19 on US Cities.” NBER Working Paper 28876. (2021)

# Motivation: What will post-Covid economic geography look like?

THE SATURDAY ESSAY

**How Remote Work Is Reshaping America's Urban Geography**

Smaller cities and communities are turning into 'Zoom towns' and competing with coastal hubs as workers move to find more space and lower costs

– *The Wall Street Journal*

"[T]he remote-work revolution will eliminate the concept of a metro hub entirely, as companies embrace the reality of a permanently distributed workforce. What if the next Silicon Valley is nowhere—or, just as precisely, everywhere?"

– *The Atlantic*

**Remote work is overrated. America's supercities are coming back.**

As Lorde said: "We live in cities."

– *VOX*

# Roadmap

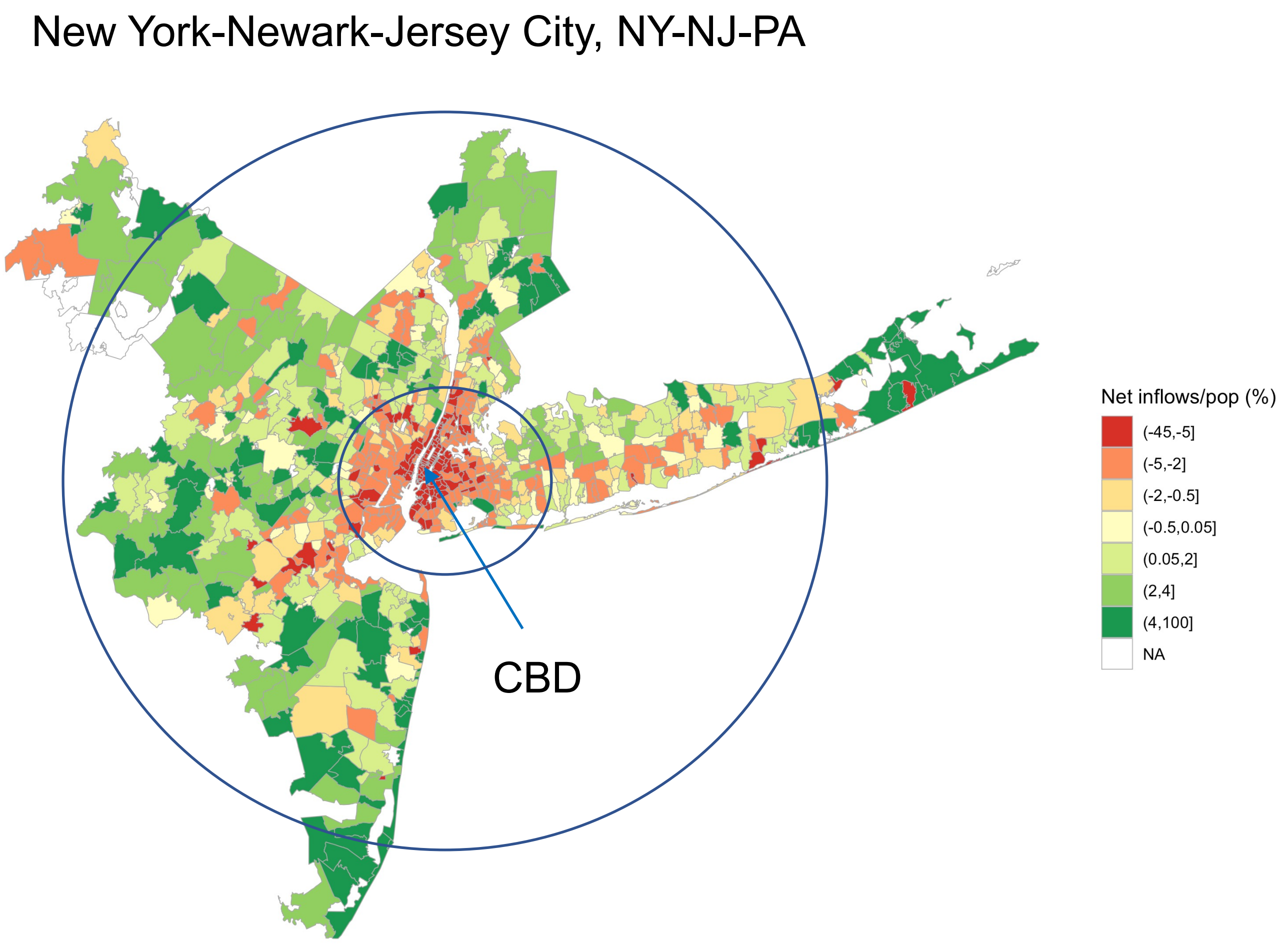
**1. Five points using data on migration patterns (USPS, Data Axle), real estate markets (Zillow), and consumption spending (Mastercard)**

A. What is the donut effect?
B. Heterogeneity across metros
C. Drivers of the donut
D. Within vs between-metro reallocation
E. Looking globally

**2. Simple model to unify facts**

**3. Policy implications for the future of cities**

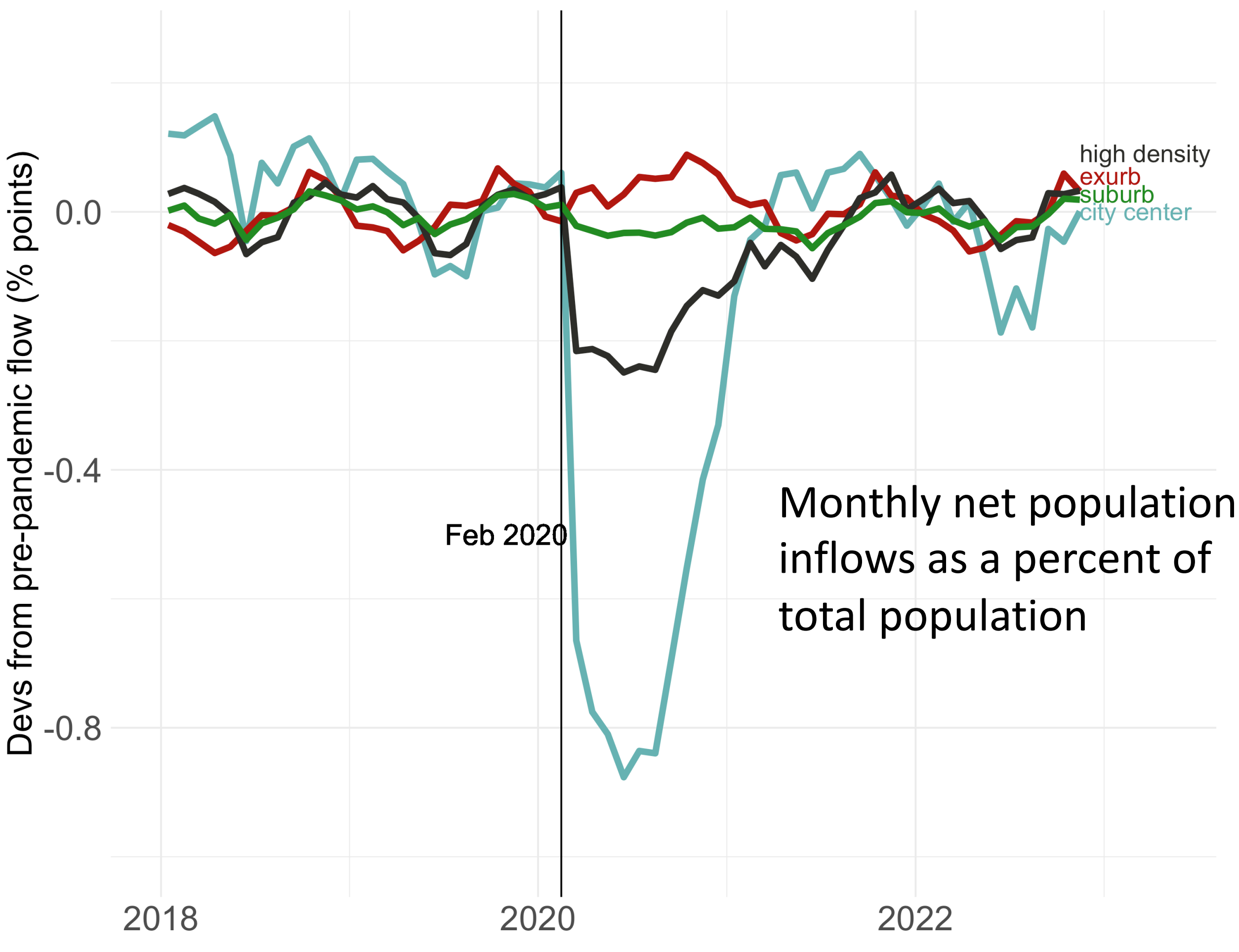
# 1. The donut effect



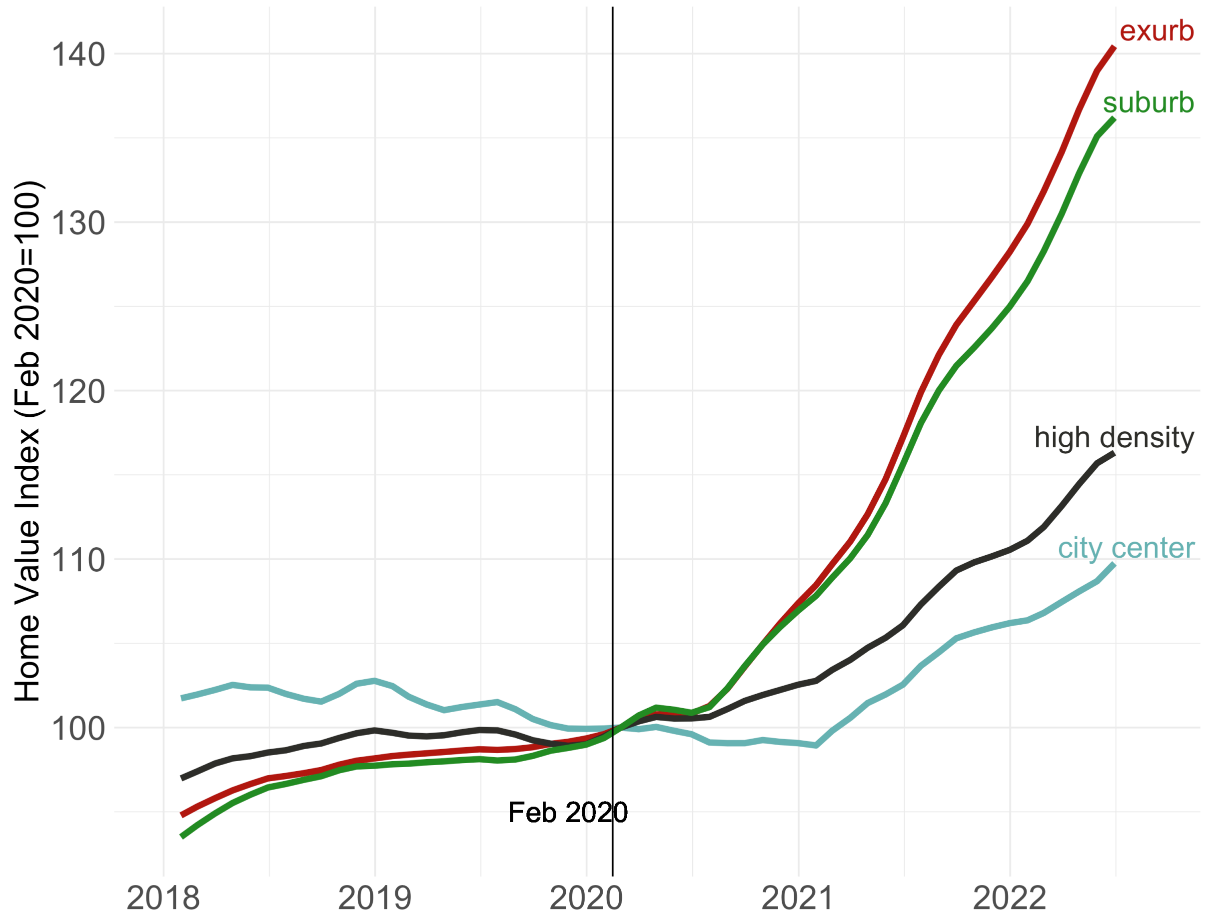

**Notes:** The heat map displays cumulative net inflows (moves in – moves out) from Feb 2020-Nov 2022 as a percent of population (2015-19 5-yr ACS) at the zipcode level for the New York-Newark-Jersey City, NY-NJ-PA MSA. Data on flows are calculated using USPS national change of address dataset. Sources: USPS, Census Bureau.

# How big is the donut?

**(a) Migration patterns – top 12 metros**

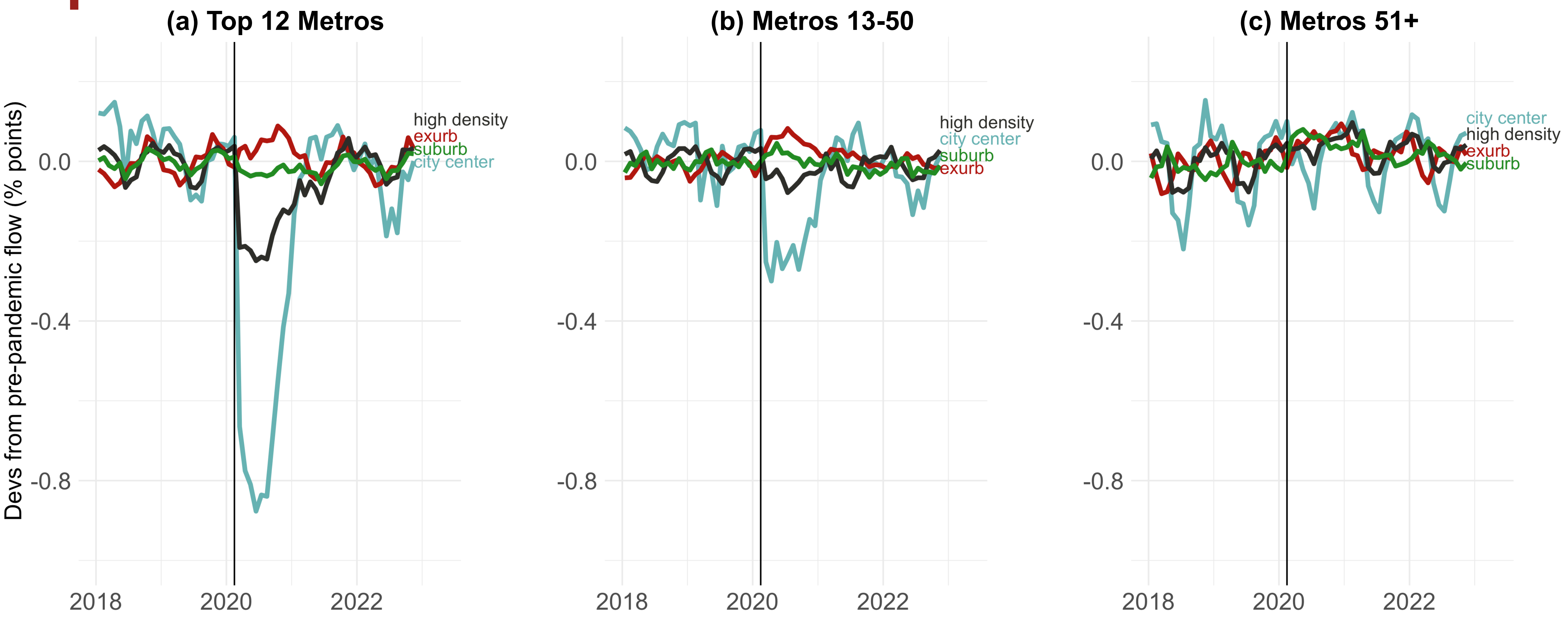



**(b) Home values – top 12 metros**




**Notes:** Left panel shows monthly net population inflows. Right panel shows Zillow's home value index. Groups are city center = CBD, High density = top 10%, mid = 50$^{th}$-90$^{th}$ percentile, low = 0-50$^{th}$ percentile. Data: USPS, Zillow, Holian (2019)

# 2. The donut effect is a big city phenomonon




- Same pattern holds when metros grouped by (i) WFH share of residents, (ii) home price level, (iii) density
- Note: High density = top 10%, mid = $50^{th}$-$90^{th}$ percentile, low = 0-$50^{th}$ percentile. Data: USPS, Holian (2019)

# 3. What explains changes in the housing market?

| | Percent change in index Feb 2020 – Feb 2022 | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Rents (1) – (4) | | | | Home values (5) – (8) | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Density | -3.049*** | | | -1.605*** | -2.561*** | | | -0.655*** |
| | (0.238) | | | (0.111) | (0.156) | | | (0.106) |
| Dist to city center | | 3.455* | | 2.123*** | | 4.718*** | | 3.787*** |
| | | (2.033) | | (0.681) | | (1.399) | | (0.162) |
| Share of 2019 residents that can WFH | | | -10.318*** | -5.501*** | | | -15.219*** | -9.910*** |
| | | | (0.306) | (0.781) | | | (0.130) | (0.865) |
| Observations | 1,031 | 1,031 | 1,031 | 1,031 | 3,583 | 3,583 | 3,583 | 3,583 |
| $R^2$ | 0.769 | 0.779 | 0.729 | 0.788 | 0.656 | 0.707 | 0.580 | 0.719 |

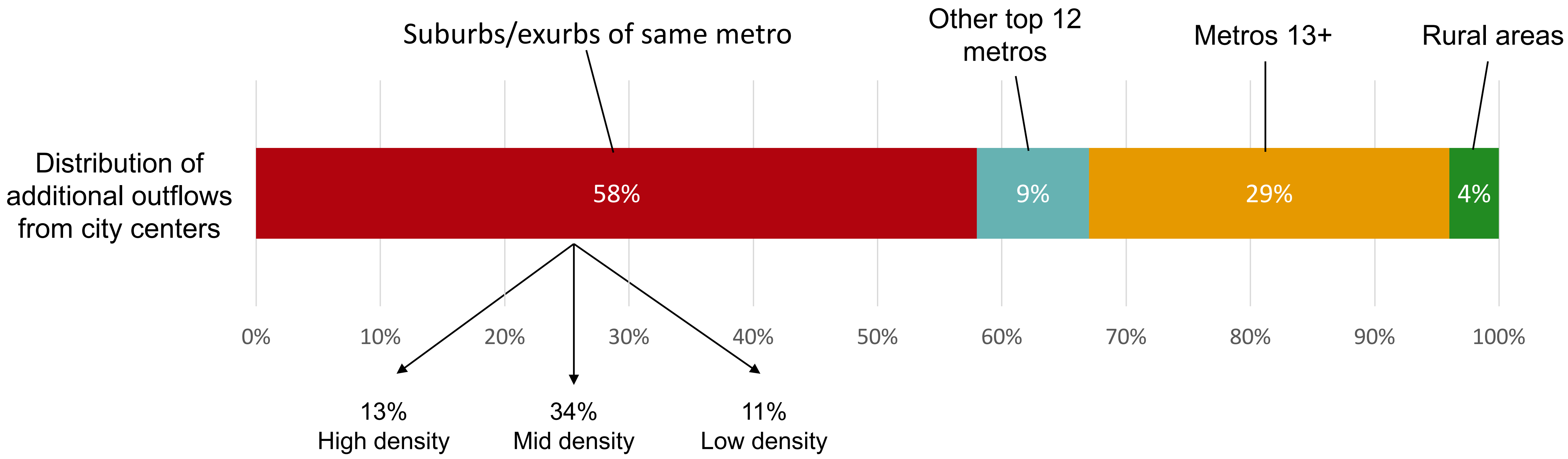
**Notes:** Population-weighted regressions of the year over year percent change in Zillow's rental index or home value index from Feb 2020 to Feb 2022 regressed on population density, distance to CBD, and the share of residents who can WFH in 2019. Controls for pre-trend and MSA fixed effects. Data limited to top 12 US metros. *p<.1, **p<.05, ***p<.01. Sources: Zillow, Census Bureau, Dingel and Neiman (2020).

# What explains changes in population/business stock?

| | Cumulative change in variable Feb 2020 – Feb 2022 as a percent of stock | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Population (1) – (4) | | | | Business establishments (5) – (8) | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Density | -1.669*** | | | -1.144*** | -2.892*** | | | -0.861*** |
| | (0.361) | | | (0.173) | (0.269) | | | (0.174) |
| Dist to city center | | 2.305* | | 0.998 | | 4.047** | | 3.353*** |
| | | (1.350) | | (3.082) | | (1.909) | | (0.213) |
| Share of 2019 residents that can WFH | | | -6.979*** | -4.805 | | | -12.757*** | -0.096 |
| | | | (0.412) | (3.051) | | | (0.279) | (1.252) |
| Observations | 3,622 | 3,622 | 3,622 | 3,622 | 3,622 | 3,622 | 3,622 | 3,622 |
| $R^2$ | 0.696 | 0.686 | 0.606 | 0.719 | 0.316 | 0.362 | 0.243 | 0.367 |

**Notes:** Population-weighted regressions of the cumulative net population inflow from Feb 2020 to Feb 2022, as a share of pre-pandemic opulation, regressed on population density, distance to CBD, and the share of residents who can WFH in 2019. Controls for pre-trend and MSA fixed effects. Data limited to to top 12 MSAs. Sources: Zillow, Census Bureau, Dingel and Neiman (2020).

# 4. Donut movers tend to stay nearby




**Notes:** The table shows the distribution of household moves post-pandemic (March 2020-Dec 2021) originating from the CBDs of top 12 metros. and high density zip codes (top 10% of distribution). We subtract the distribution of moves from the same-length pre-pandemic period. Population sizes of the different buckets are: top 12 metros=94.5m, metros 13-365=176m, rural=57m. Sources: US Postal Service, Data Axle, US Census Bureau.

# The donut is driven by increased outflows

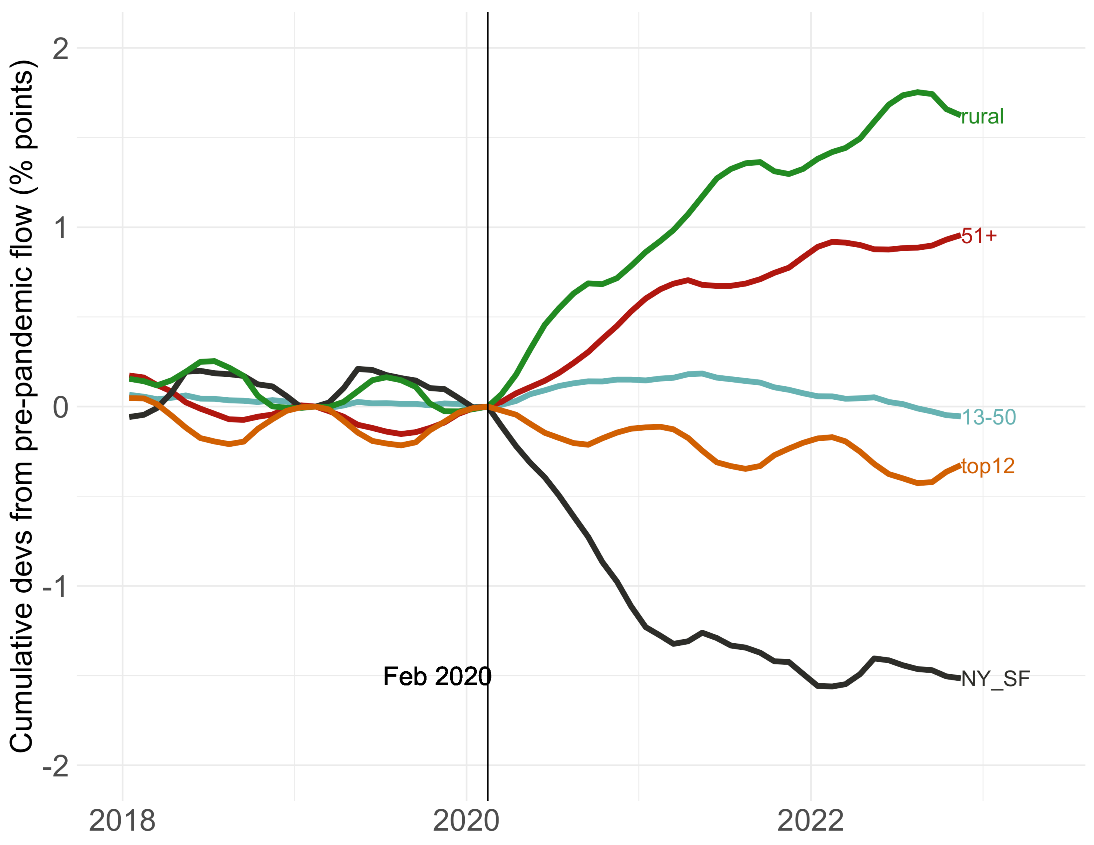
| Move type | Within | | | Between | | | Total |
|---|---|---|---|---|---|---|---|
| Metro type | High | Mid | Low | Top 12 | Other | Non Metro | |
| Outflows | -0.33% | -0.28% | -0.85% | -0.23% | -0.73% | -0.11% | -2.53% |
| Inflows | 0.28% | 0.04% | -0.06% | -0.04% | -0.03% | -0.01% | 0.17% |
| Net outflows | -0.61 | -0.32% | -0.79% | -0.19% | -0.7% | -0.1% | -2.7% |

**Notes:**

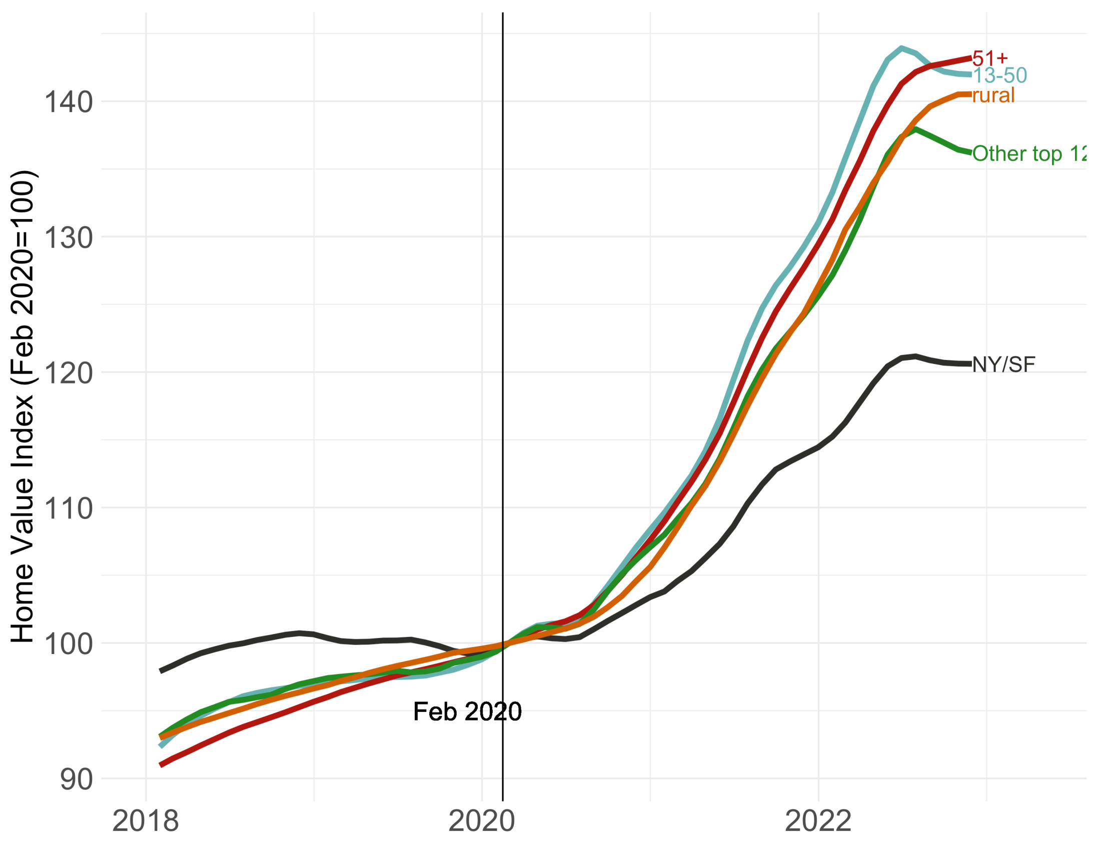
- The table shows the distribution of household moves post-pandemic (March 2020-Dec 2021), differenced from pre-pandemic flows (June 2018-March 2020) to and from the CBDs of top 12 metros, as a share of CBD population.
- Shown as a percent of CBD population, with respect to the CBD – *negative values mean CBD population losses*
- Population sizes of the different buckets are: top 12 metros=94.5m, other metros=176m, rural=57m. Sources: US Postal Service, Data Axle, US Census Bureau.

# Still, there were sizable cross-metro flows, with NY and SF most affected

### (a) Cumulative net population inflows

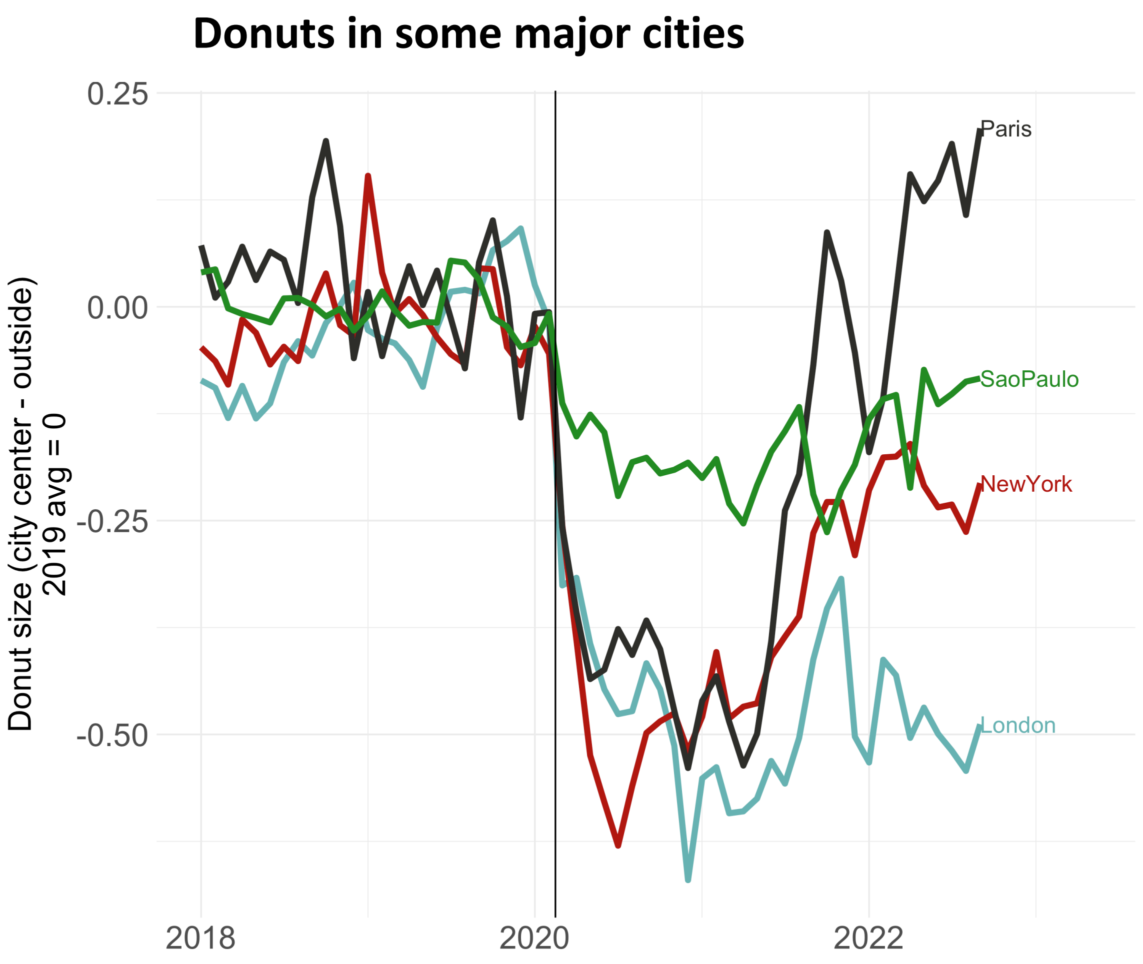


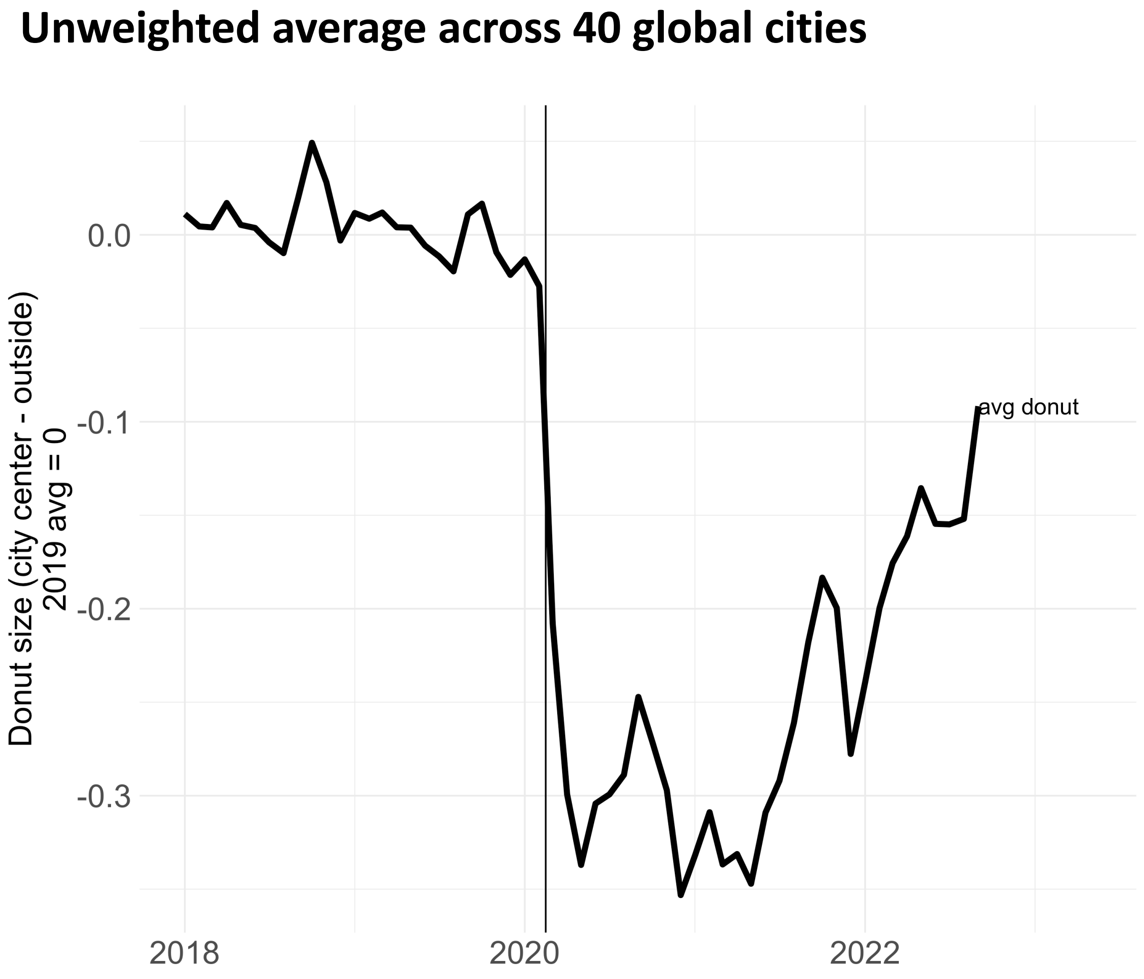

### (c) Home value index




**Notes:** Each panel groups the data into four buckets of MSAs by total population: NY and SF, the other top 12 MSAs, MSAs 13-50 and MSAs 51+. The population sizes of the different buckets are: top 12 metros=94.5m, metros 13-365=176m, rural=57m. Sources: USPS, Zillow, Census Bureau. Data: Jan 2018 – Nov 2022.

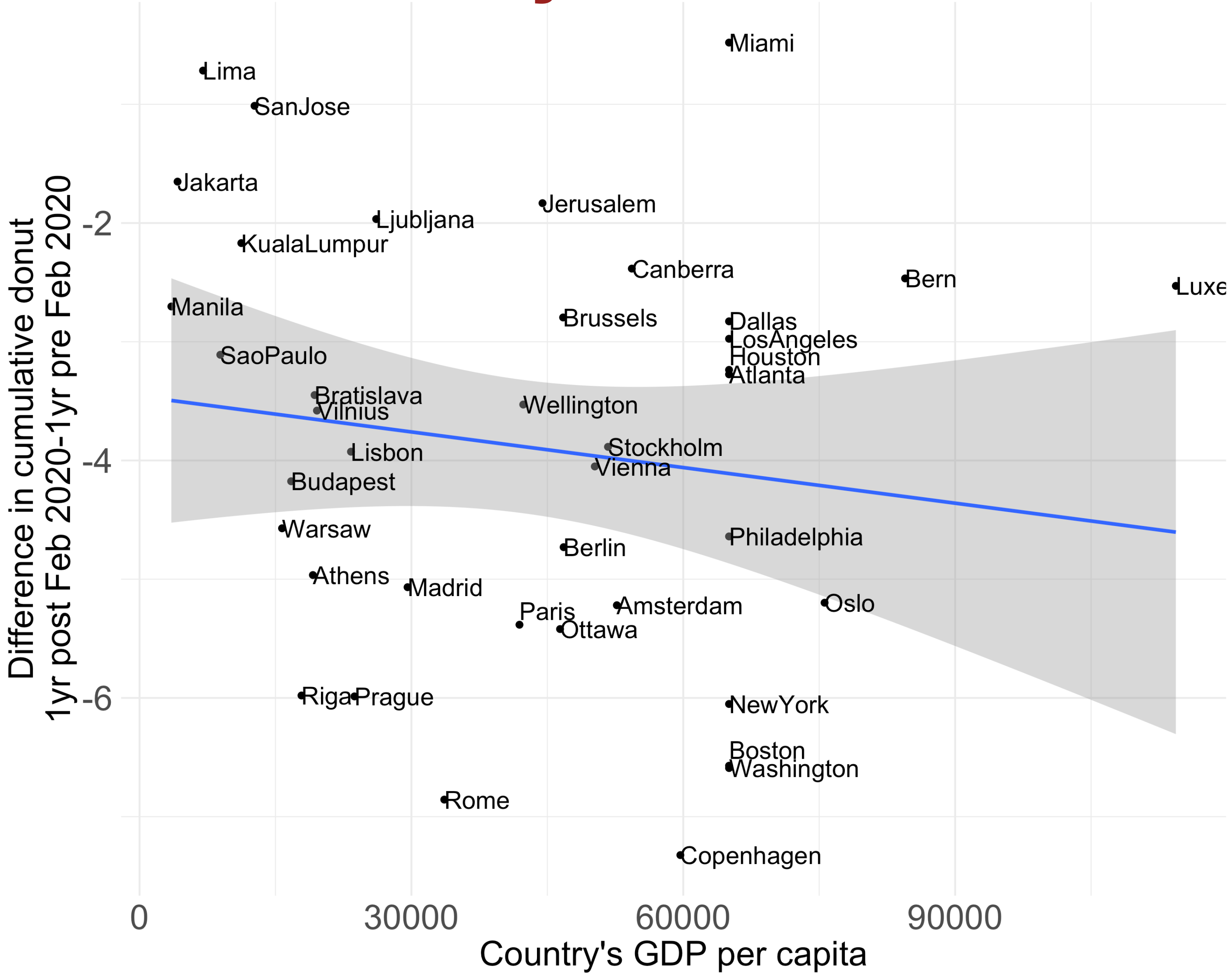
# 5. The donut effect is present internationally




**Notes:** Current Mastercard data covers 40 global cities; donut represents monthly transaction value plotted as a difference in deviations from the 2019 average (CBD – outside). CBDs defined by pulling coordinates of “city hall” and “city center” from Google Maps. Alcedo et al (2022) describes and validates the data

# What explains cross-city variation in the donut?




**Notes:** Mastercard data for a sample of 40 global cities; donut represents deviations from 2019 average (CBD – outside)

# Unifying our facts: a toy model

- 2 metro areas, one big and one small. A city and suburb in each: Big: $a_1, a_2$; Small: $a_3, a_4$
- Individuals choose locations to maximize utility, a function of wages, commute costs, amenities, and rents: $u_i = w_i^{\beta} c_i^{-\theta} a_i^{\gamma} r_i^{-\beta}$
- Differences between locations are given by: (a) productivity: $w_l > w_s$ (b) amenities: $a_1 > a_2 = a_3 > a_4$
- Variables:
  - $1 - \pi =$ share of days WFH
  - $\theta, \beta =$ elasticity of utility with respect to commute costs and net income (wages – rents)
  - $\epsilon =$ elasticity of rents with respect to population
- Simulate 2 worlds, full remote work and hybrid remote work
  - Hybrid work halves commute costs; full-time remote work drives commute costs to 0

| Average commute costs | | | | |
|---|---|---|---|---|
| | Large metro (New York) | | Small metro (Indianapolis) | |
| | City center | Suburb | City center | Suburb |
| Full remote work | 0 | 0 | 0 | 0 |
| Hybrid remote work | $\pi$ | $\pi x$ | $\pi$ | $\pi x$ |
| No remote work | 1 | $x$ | 1 | $x$ |

# Hybrid work vs fully remote shocks

## Comparative statics

- Solve for spatial equilibrium by equating utility across locations pairwise
- Table below shows the differences both between and within metros

| | Within-metro reallocation | Between-metro reallocation |
|---|---|---|
| WFH model | $\Delta(n_1 - n_2) + \Delta(n_3 - n_4)$ | $\Delta(n_1 + n_2 - n_3 - n_4)$ |
| Hybrid WFH | $\frac{(1-\pi)4\theta(x-1)}{\beta\epsilon}$ | **0** |
| Full-time WFH | $\frac{4\theta(x-1)}{\beta\epsilon}$ | $\frac{2(w_1 - w_2)}{\epsilon}$ |

# Main results and an interpretation

**Key facts:**

1. Persistent donuts, well into end-2022. Stabilization of work-from-home (30% of days) suggests donuts are here to stay
2. Sizable heterogeneity across metros
3. Most movers stay nearby, but not all. There are sizable cross-metro flows, especially out of NY and SF. Broadly consistent with Su and Liu (2021) and Gupta et al (2022)

**Interpretation:** World of persistent hybrid work (30%), some full-time remote work (13%), some between-metro job-switching (LODES data shows bump in cross state job-switchers).

**Further work:**

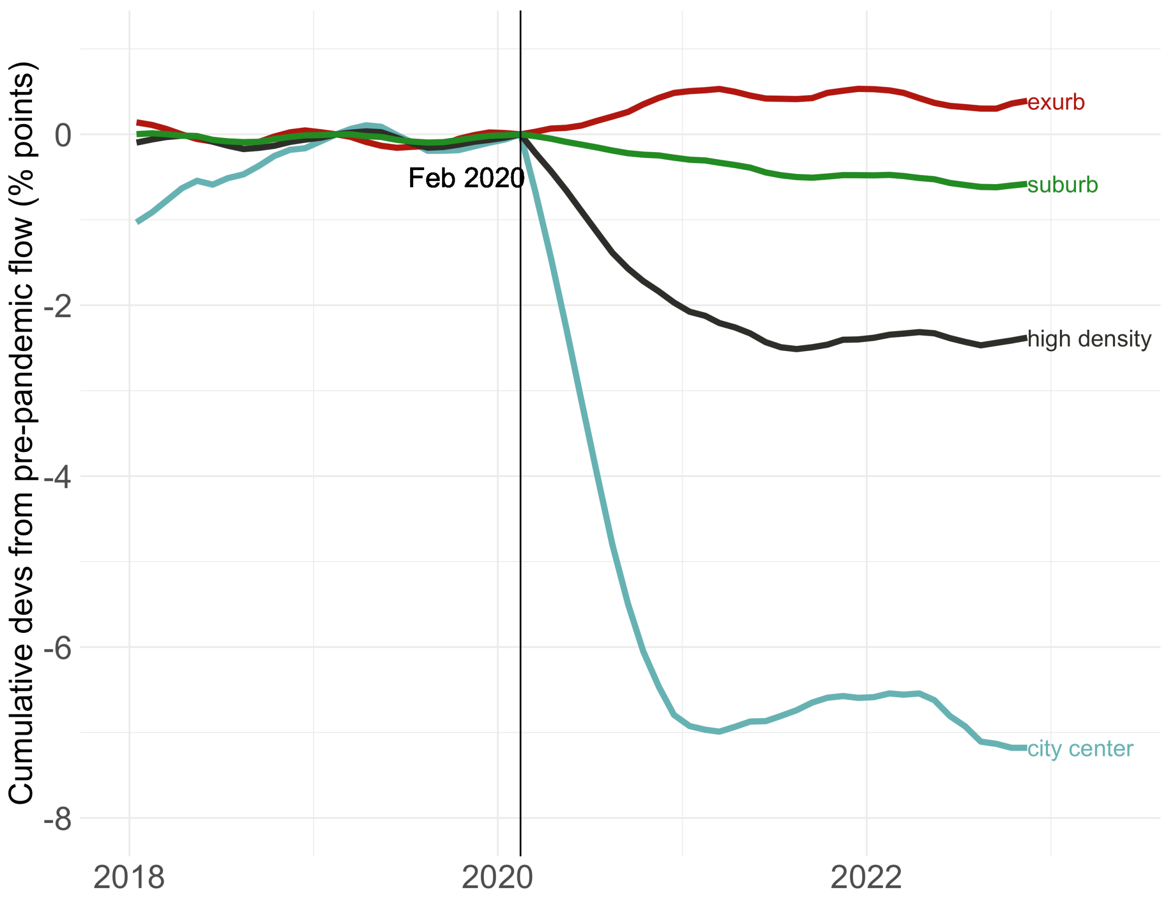
1. Look at commuting distances. LODES data released on a lag
2. Decompose movers between job-switchers and job-stayers
3. Include measures for the value of amenities

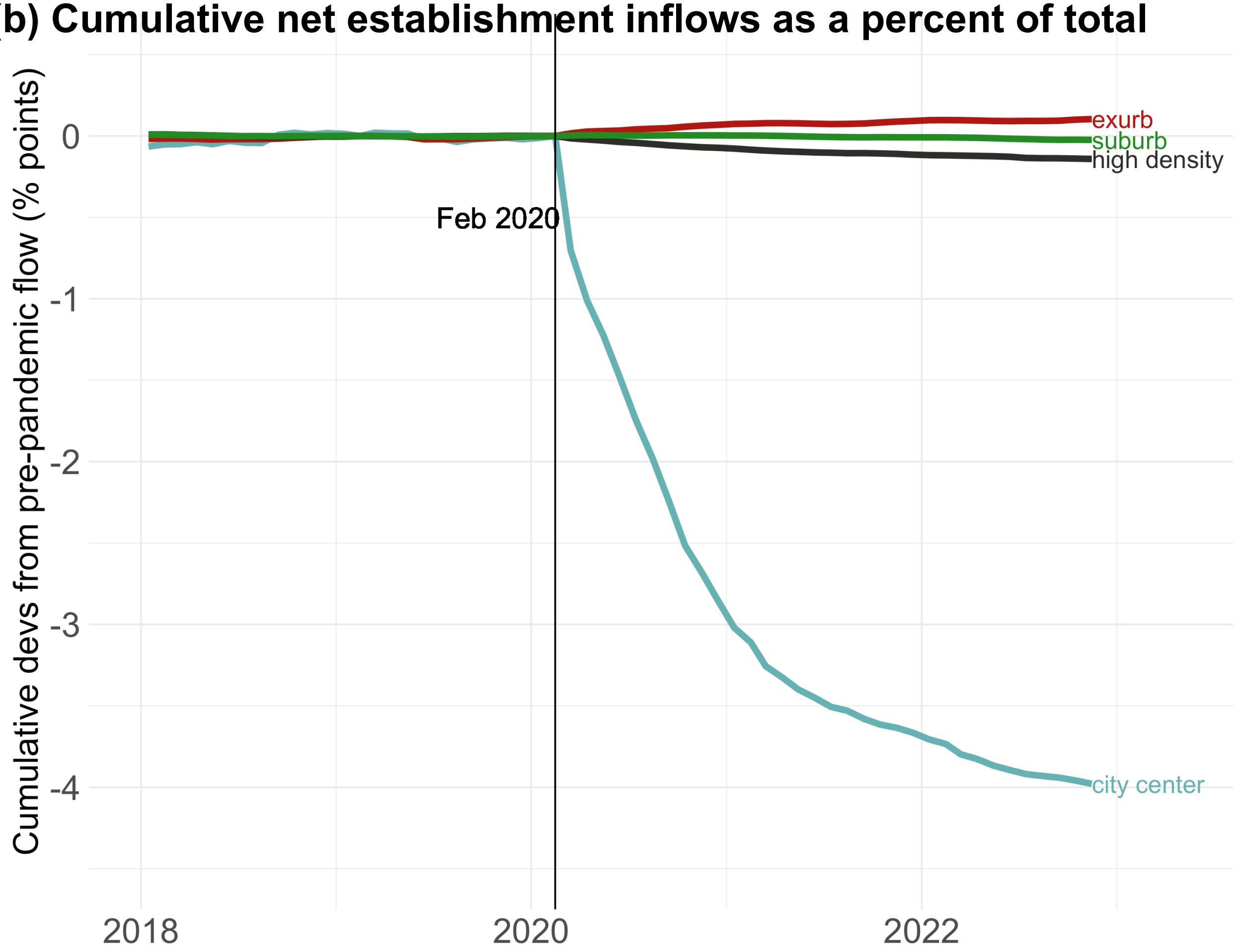
# Implications of the donut

1. Public transport across cities are down; unlikely to recover.
2. Office occupancy down (~50%, Kastle Securities). Opportunity to rezone space/build more housing to make cities more livable.
3. That will strain city government tax revenues. Incentive for better governance.
4. New York as a case study
   A. Reduced subway frequency on Monday/Friday
   B. Mayor and Governor collaborating on plan to rezone space
   C. See this week's *Economist* (which cites Stijn's work)

# Appendix

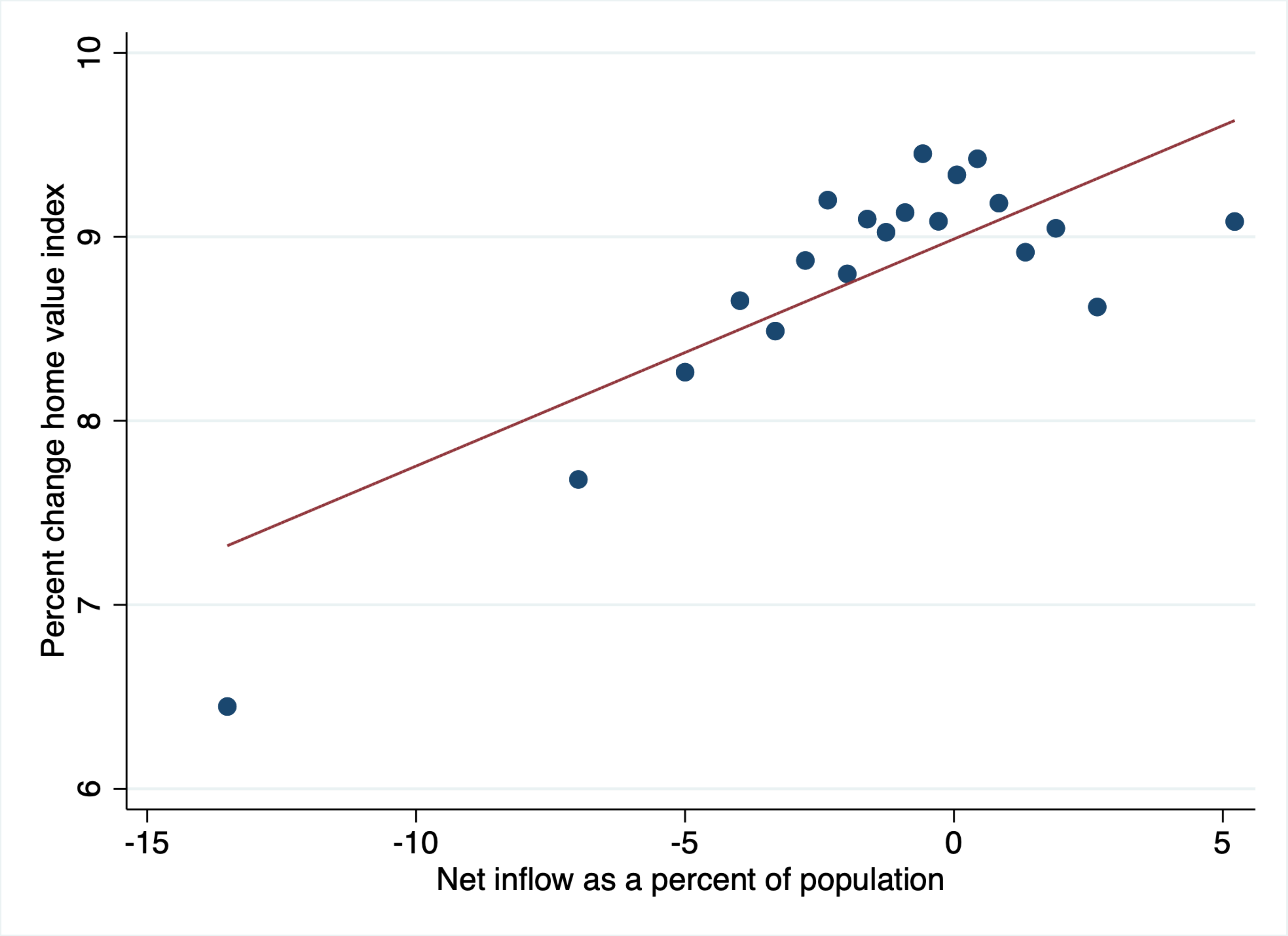
## Appendix A5: Cumulative flows versus the pre-pandemic trend follow the donut effect with sharp outflows from CBDs




**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 of movers from Data Axle, 1.7 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 from the average flow in the year pre-pandemic. 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%, suburb = 50-90$^{th}$ percentile, exurb = 0-50$^{th}$ percentile. The city center is defined by taking all zipcodes with centroids contained within a 2 km radius of Central Business District coordinates taken from Holian (2019). Sources: USPS, Census Bureau, Holian (2019). Data: Jan 2018 – Nov 2022.

# Migration flows drive real estate price changes

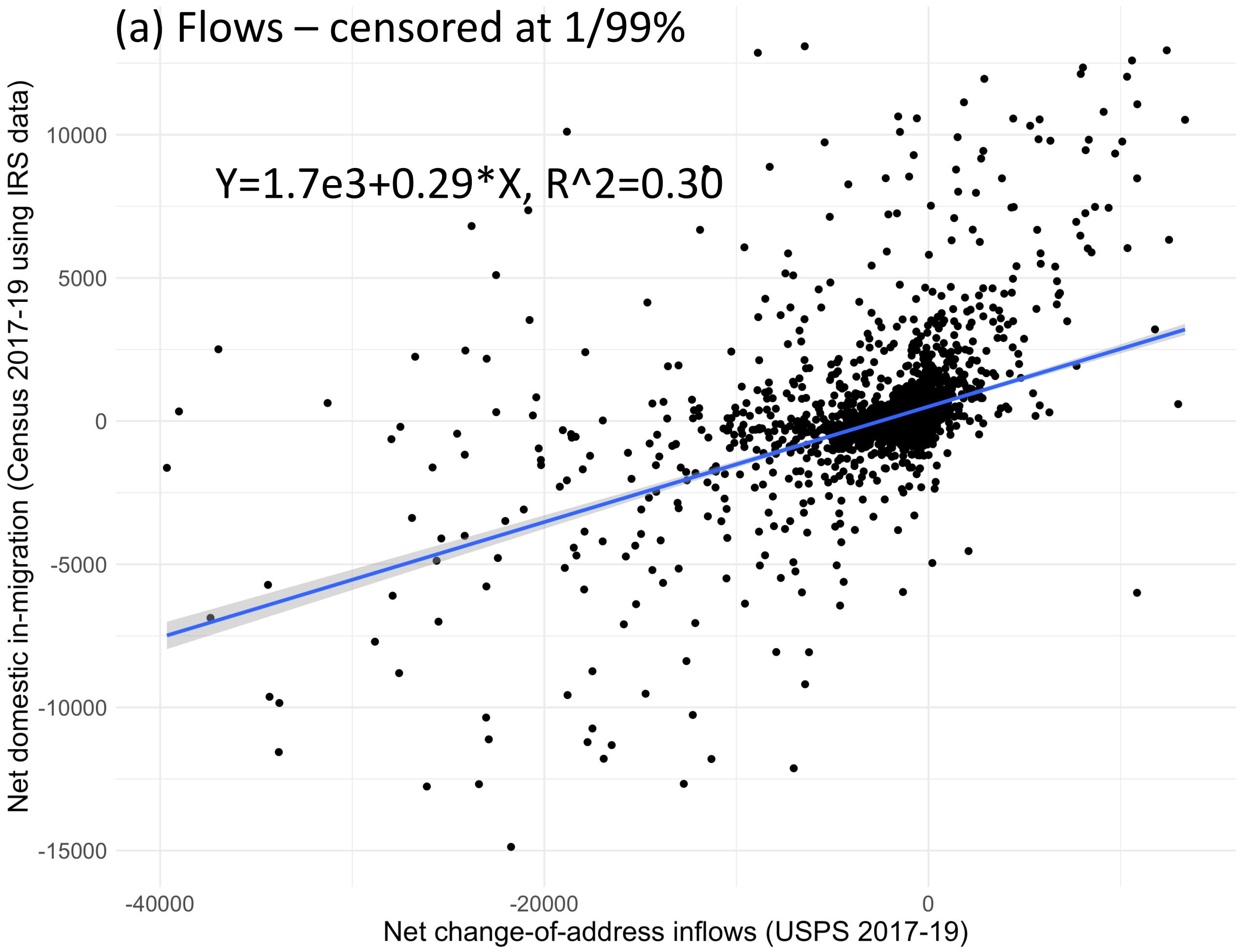


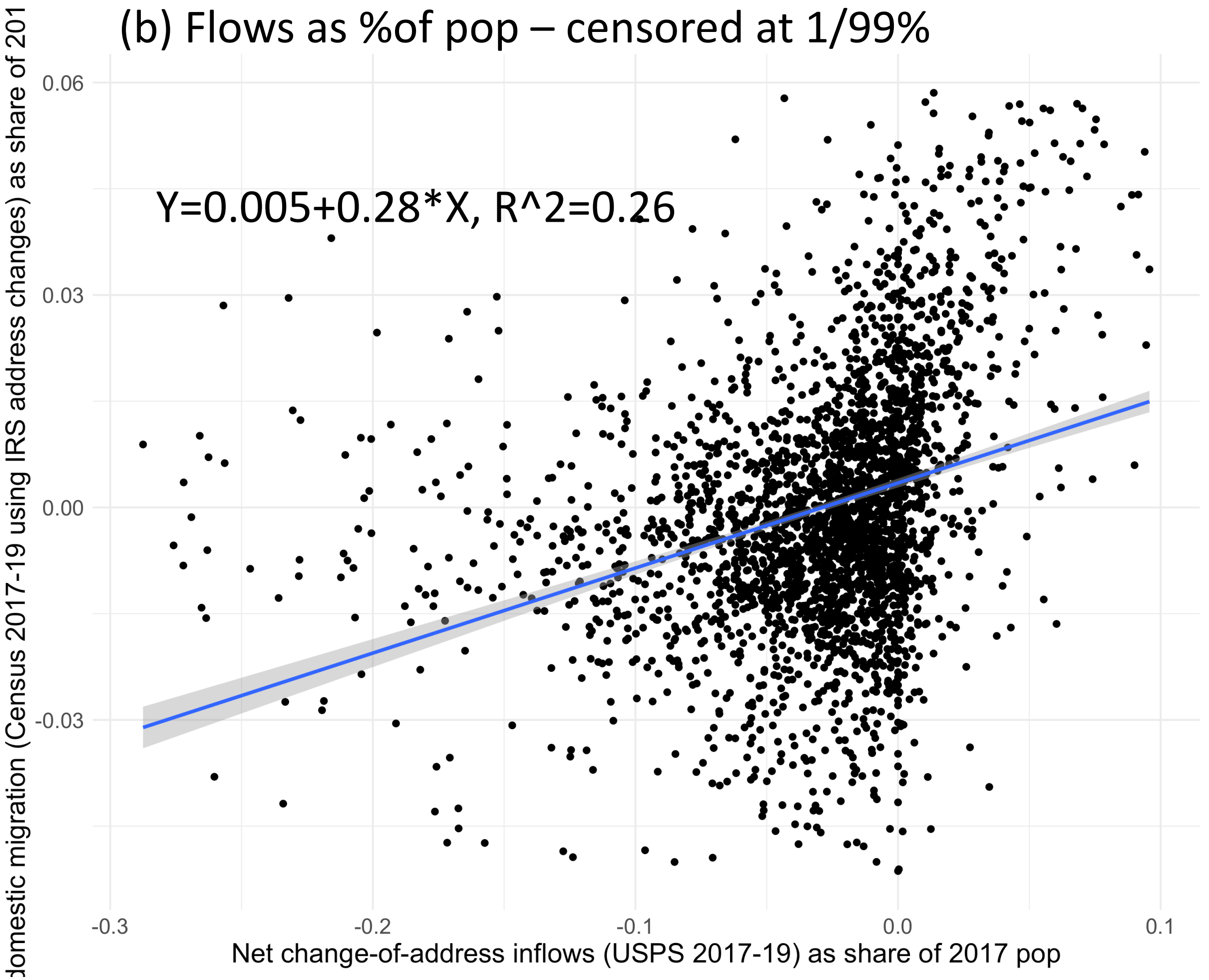

**Regression estimates**

- A 1pp increase in net inflows is associated with a .2pp to .5pp increase in home values

- Adds evidence to theory that it is actual migration contributing to real estate trends instead of differential income shocks, interest rates, or changing preferences in terms of housing

# Appendix A7a: USPS Change of address flows follow official Census migration statistics

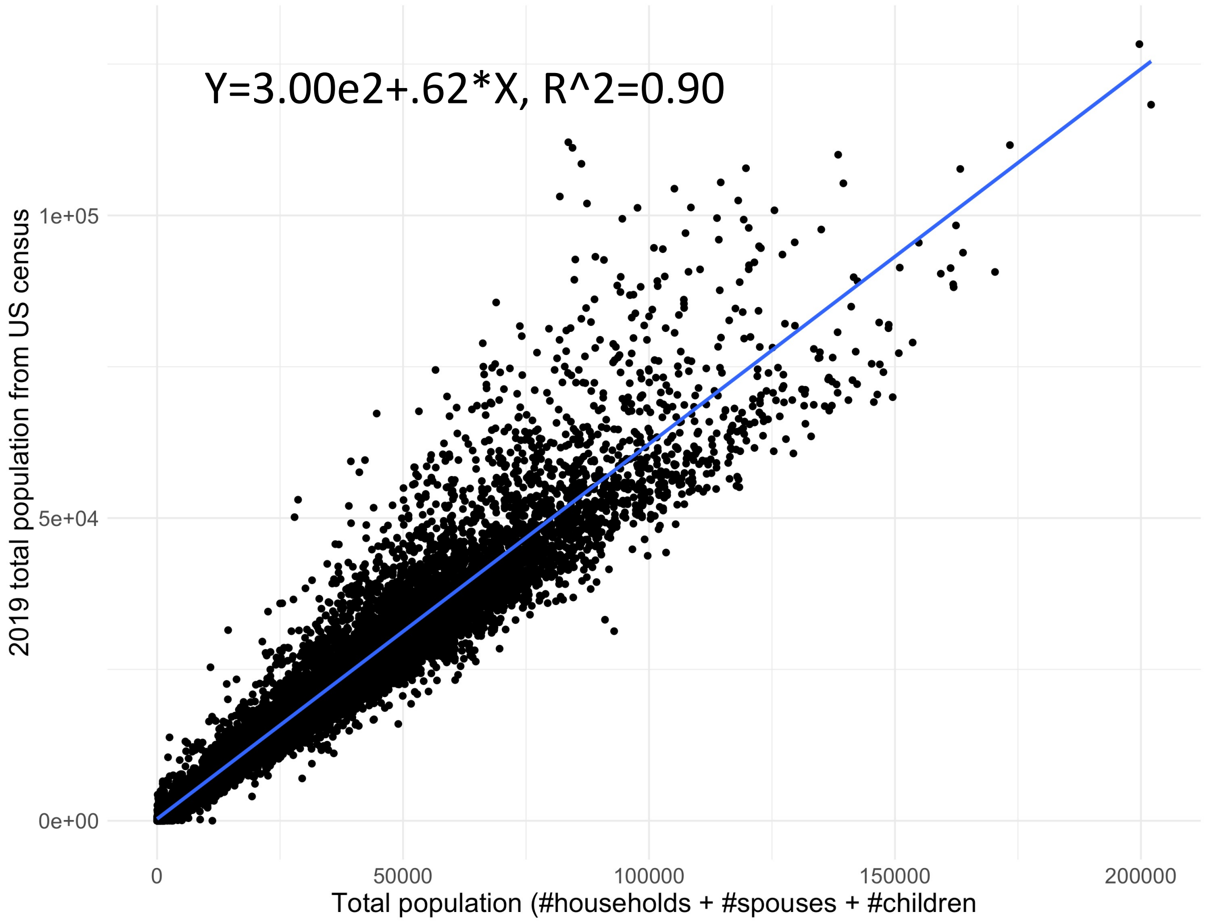


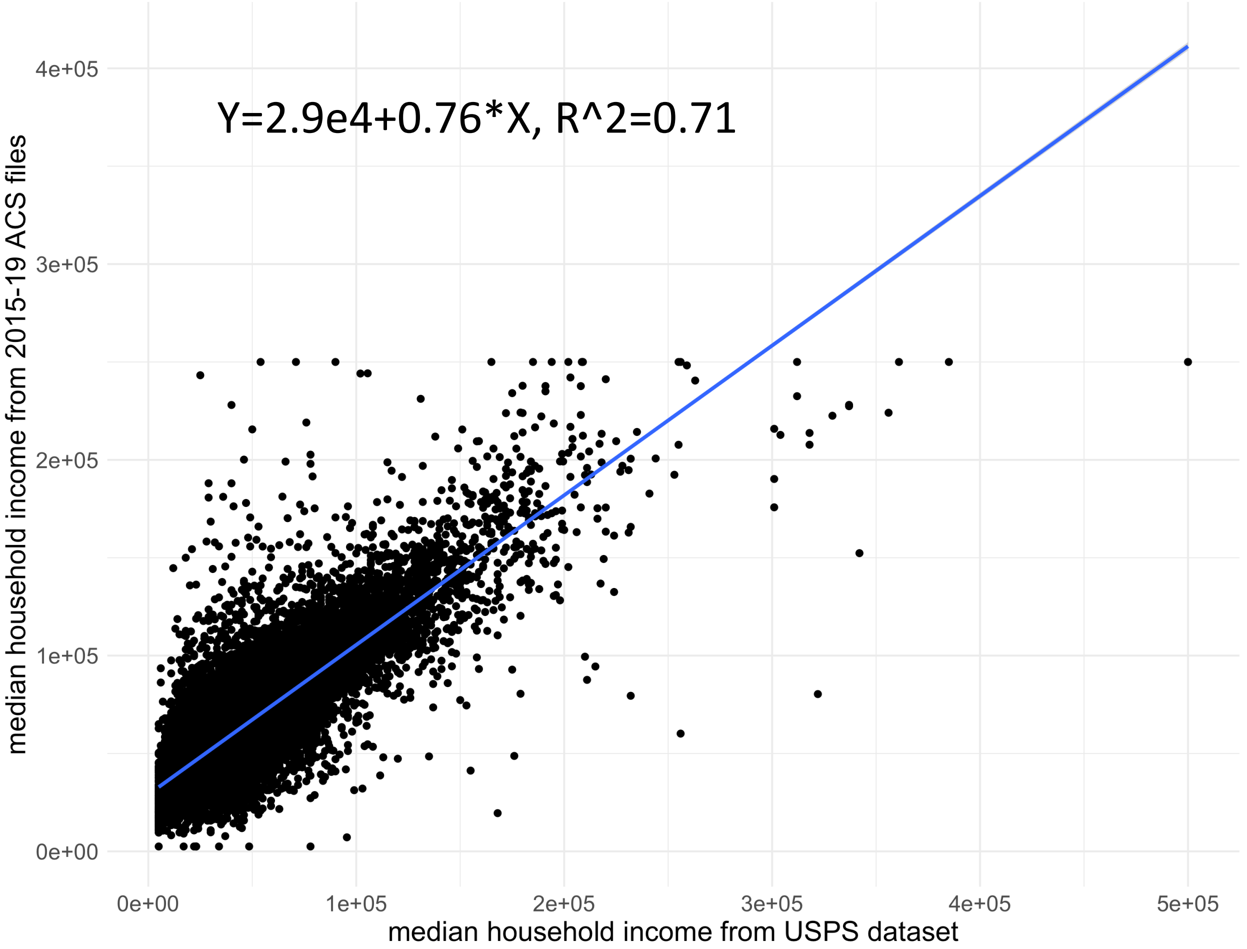

**Notes:** This chart shows a county level scatterplot and regression of official migration vs change-of-address flows. The y-axis is the county-level net domestic in-migration from 2017-19 taken from the US Census Bureau. The x-axis is the net population inflow as measured by USPS change-of-address data. 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. Note that USPS data do not include inflows from other countries. Sources: USPS, Census Bureau.

# Appendix A7b: Data Axle levels match ACS levels for population and income

## (a) Population levels



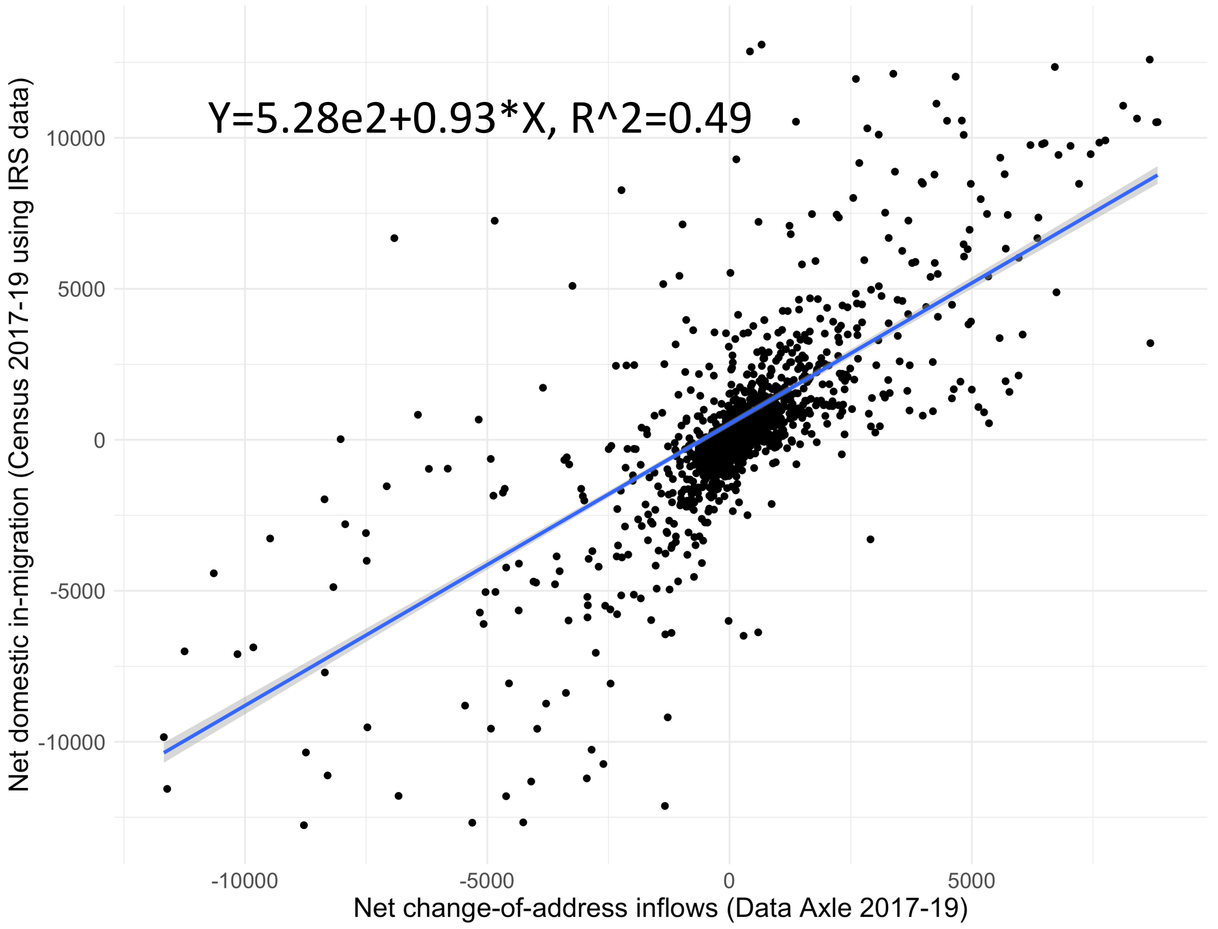

## (b) Median household income



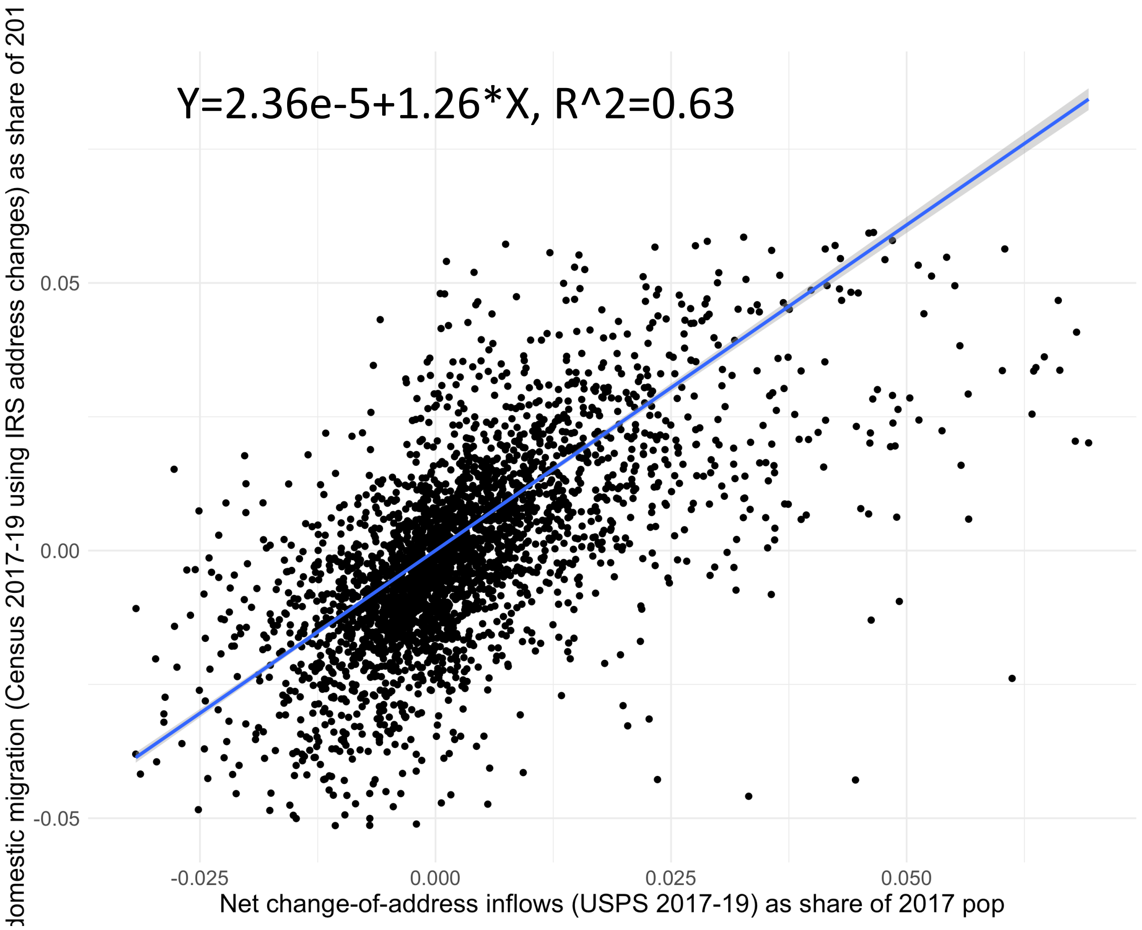

**Notes:** This chart shows a county level scatterplot and regression of official population and income data from the 2015-19 pooled American Community Survey (ACS) vs linked population and income data constructed from Data Axle address files. The y-axis is the (a) county-level population or (b) median household income taken from ACS data. The x-axis is the (a) county-level population or (b) median household income from Data Axle's household-address files. Sources: Data Axle, American Community Survey, Census Bureau.

# Appendix A7c: Data Axle flows follow official migration statistics

(a) Net inflow– censored at 1/99%

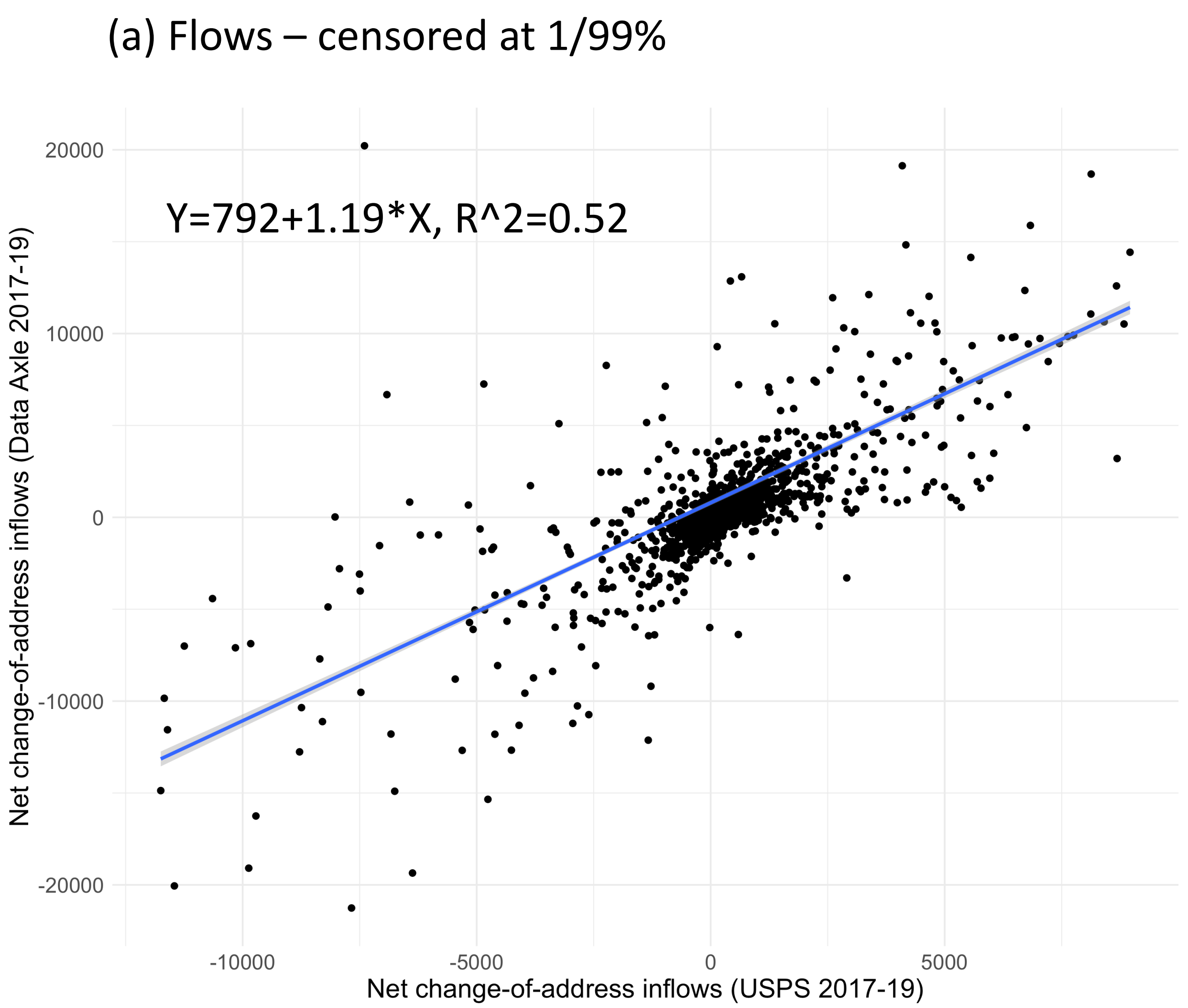


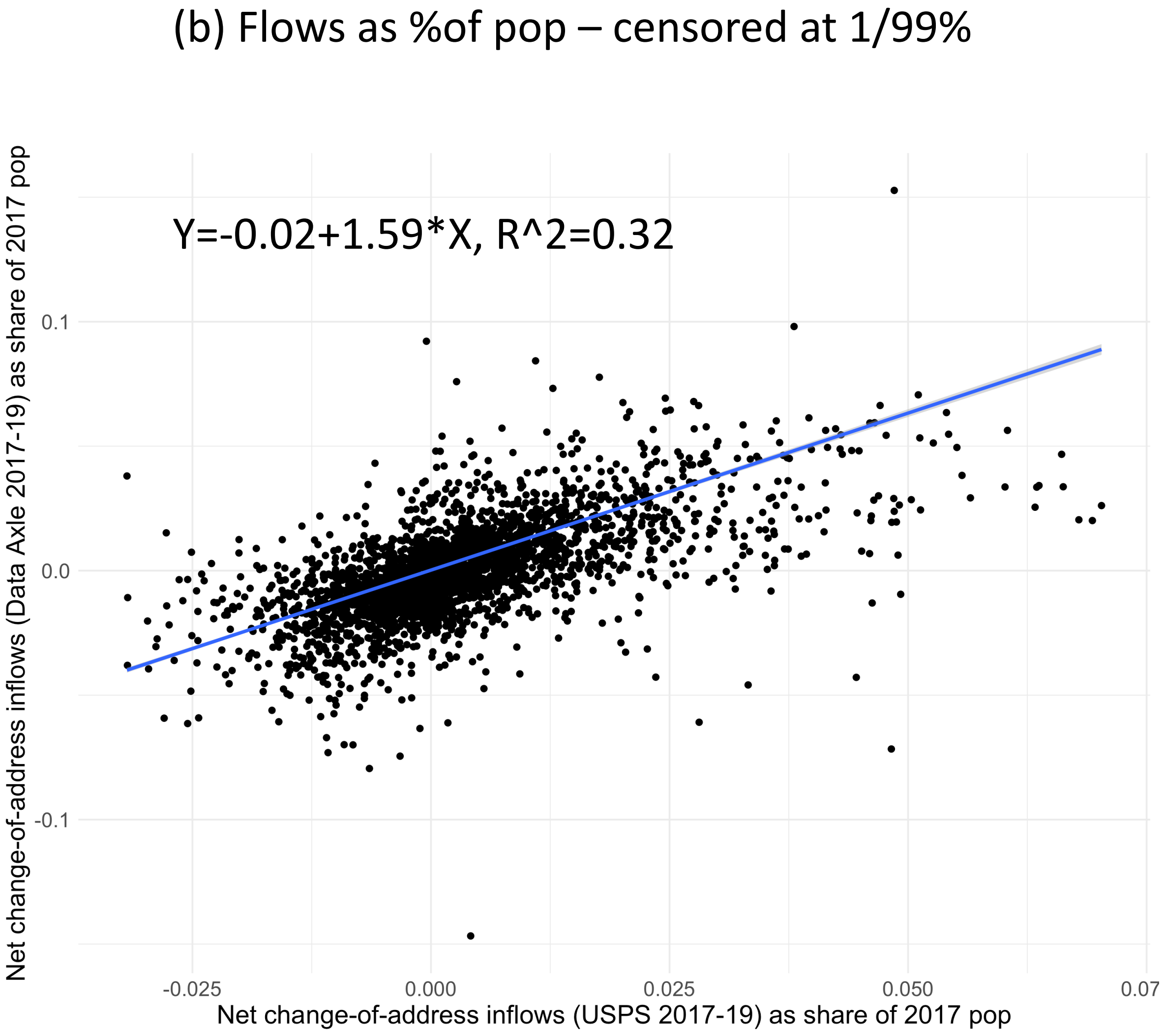

(b) Flows as %of pop – censored at 1/99%




**Notes:** This chart shows a county level scatterplot and regression of official migration vs change-of-address flows. The y-axis is the county-level net domestic in-migration from 2017-19 taken from the US Census Bureau. The x-axis is the net population inflow as measured by linked address level files provided by Data Axle. We calculate population flows by summing the head of household, spouse and children for each household. Sources: USPS, Census Bureau, Data Axle.

# Appendix A7d: Data Axle flows follow public USPS flows




**Notes:** This chart shows a county level scatterplot and regression of public USPS change-of-address flows vs flows derived from Data Axles quarterly address files. The y-axis is the county-level change of address flows from the publicly available USPS files. The x-axis is the net population inflow as measured by linked address level files provided by Data Axle. We calculate population flows by summing the head of household, spouse and children for each household. Sources: USPS, Census Bureau, Data Axle.