The City Paradox: Skilled Services and Remote Work*

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Abstract

Large cities in the US are the most expensive places to live. Paradoxically, this cost is paid disproportionately by workers who could work remotely, and live anywhere. The greater potential for remote work in large cities is mostly accounted for by their specialization in skill- and information-intensive service industries. We highlight that this specialization makes these cities vulnerable to remote work shocks. When high-skill workers begin to work from home or leave the city altogether, they withdraw spending from local consumer service industries that rely heavily on their demand. As a result, low-skill service workers in big cities bore most of the recent pandemic's economic impact.

Keywords: Remote Work, High-skill Services, Technological Change
JEL Codes: O33, R11, R12

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I. The City Paradox

Cities in the 21st century exhibit a paradox. Despite being the densest and most expensive places to live, a disproportionate fraction of their inhabitants work jobs that could be done from anywhere.

We use the occupation-based work-from-home classification introduced by Dingel and Neiman (2020) to show the work-from-home specialization of U.S. cities. Figure 1 plots the fraction of jobs that can be done remotely against commuting zone population density. The relationship is striking: the denser a city, the more work can be done remotely. In America's densest cities, around 45 percent of local jobs can be done from home, corresponding to about 60 percent of the local payroll. The difference between the left and the right panel reveals that work-from-home jobs pay higher wages on average.

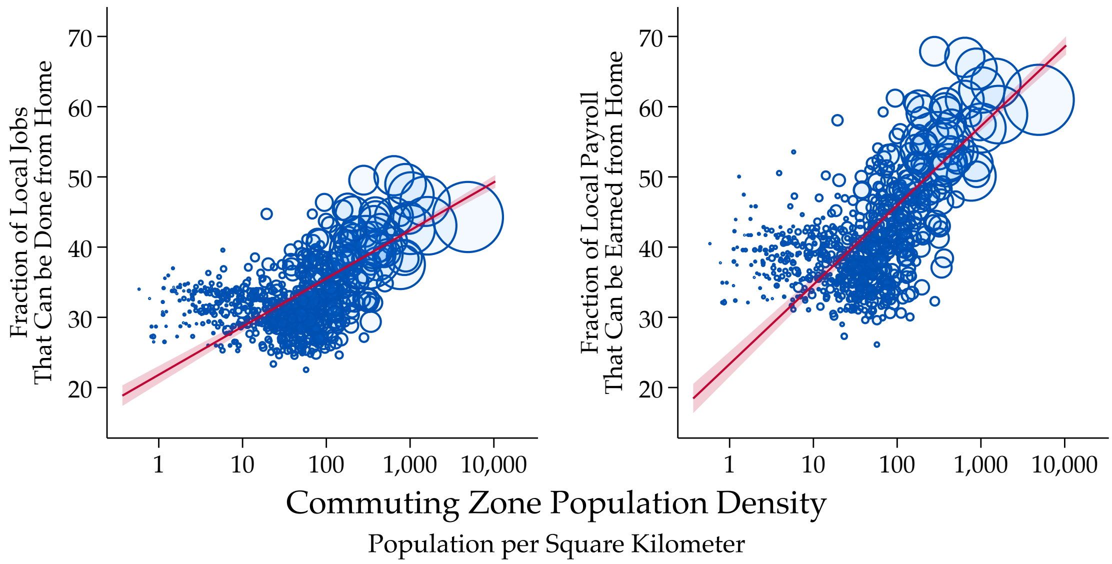
Cities contain many jobs that can be done from home due to their specialization in a particular class of skill- and information-intensive services, which in other work we have called Skilled Scalable Services (see Eckert, Ganapati, and Walsh, 2020b). These Skilled Scalable Services (SSS) comprise four 2-digit NAICS industries: Information (NAICS 51), Finance and Insurance (NAICS 52), Professional Services (NAICS 54), and Management of Companies (NAICS 55).

Table 1 shows that these four industries account for the greater potential for remote work in large cities. Column 1 shows the relationship between commuting zone density and the share of jobs that can be done from home. Column 2 shows that population density no longer has a relationship with local work-from-home specialization after controlling for the local SSS employment share. Furthermore, the R-squared rises from 0.1 to 0.8: the remote work specialization of large cities is mostly accounted for by SSS. Column 3 shows that adding the employment share of all 1-digit NAICS industries to the specification in Column 1 does not improve the regression fit: industrial structure beyond SSS industries does not help to explain cities' work-from-home specialization further. It is also not the case that more jobs *within* SSS industries can be done from home in denser cities (see Column 4, which separately interacts SSS employment share with local population density). The fraction of college workers in the local labor force adds some additional explanatory power (see Column 5) but appears to mainly pick up that SSS industries are more skill-intensive.[1]

At first blush, the concentration of remote work jobs in cities is surprising. Average

[1] We show in Eckert, Ganapati, and Walsh (2020b) that SSS industries have a disproportionate fraction of college workers among their workforce. SSS are also characterised by intensive and increasing use of ICT, which allows for their remote delivery. Other work that is performed by college workers may not have this characteristic (e.g., doctors).

FIGURE 1: THE CITY PARADOX



Notes: We use data from the pooled American Community Survey from 2014-2018. We drop data for Alaska, Hawaii, and Washington, D.C., from our sample. The sample contains 722 commuting zones as defined by Tolbert and Sizer (1996) covering the entire territory of the states in the sample. We use the "work-from-home" classification by Dingel and Neiman (2020). The figure also shows the fitted line of a population-weighted OLS regression.

wage levels are increasing in city size, and even within cities, wages are increasing with density (see Acosta, Eckert, Liang, and Walsh, 2020). Firms pay their workers a density premium, while it seems that many of those jobs could be performed remotely. As a result, an extensive literature has argued that density must bestow a productive advantage that is not mitigated by the current level of communication technology. After all, if it did not, why would firms not simply locate elsewhere?

However, while many urban jobs can be done from home in theory, practically none were done from home until the emergence of COVID-19. During the pandemic, many of the workers Dingel and Neiman (2020) predicted to be able to work from home actually started working remotely (see, e.g., Bartik, Bertrand, Cullen, Glaeser, Luca, and Stanton, 2020; Bick, Blandin, and Mertens, 2020), bringing the city paradox to the fore. The pandemic was a shock that drastically increased the costs of working in the office.[2]

Beyond documenting the City Paradox, this paper traces its implications for cities' labor markets during the recent work-from-home shock. We show that big cities' SSS-specialization makes them vulnerable to remote work shocks like the pandemic. When SSS workers start working from home or leaving the city to work from elsewhere, their spending on consumer services in the local economy decreases or disappears.

[2] As Glaeser, Gorback, and Redding (see 2020) show workers leaving home substantially increased their risk of contracting Covid-19.

This decrease is a key channel through which the pandemic affects low-skill service workers that work in consumer services industries in big cities.

TABLE 1: SKILLED SCALABLE SERVICES SPECIALIZATION AND THE CITY PARADOX

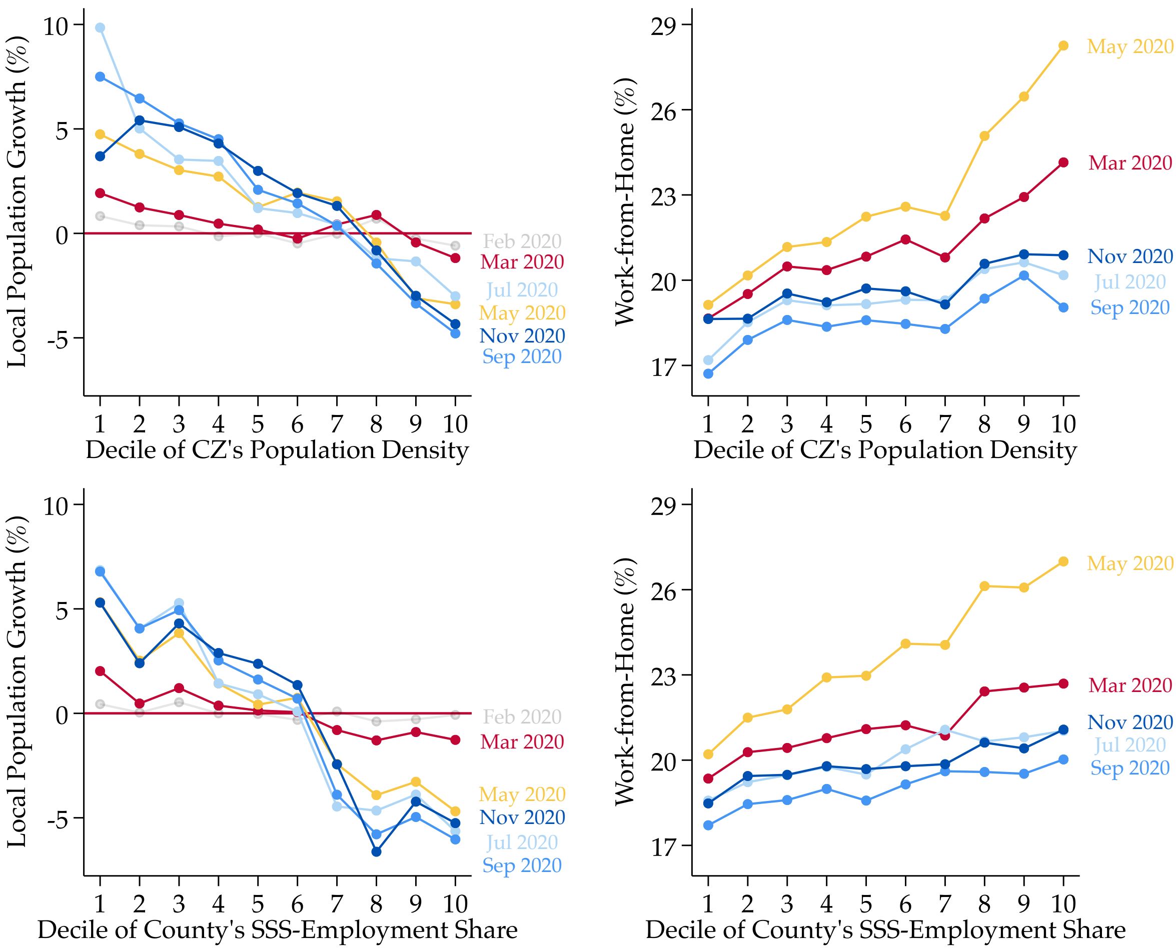
	Log of Fraction of Local Jobs That Can be Done from Home				
	(1)	(2)	(3)	(4)	(5)
Log Poulation Density	0.027***	-0.003	-0.007***	-0.002	-0.005***
	(0.004)	(0.002)	(0.003)	(0.009)	(0.001)
SSS Employment Share		3.947***		4.014***	1.804***
		(0.126)		(0.487)	(0.189)
Log Population Density × SSS Employment Share				-0.015	
				(0.092)	
College Employment Share					1.257***
					(0.108)
Local NAICS1 Employment Shares	No	No	Yes	No	No
Adjusted R-squared	0.087	0.755	0.763	0.755	0.860
Observations	722	722	722	722	722

Notes: The source of data is the American Community Survey 4 year files for 2014-2018. We use the "work-from-home" classification by Dingel and Neiman (2020). The table shows the output of five regressions run for 722 commuting zones level (see Tolbert and Sizer, 1996) covering the entire territory of the United States. We drop Hawaii, Alaska, and Washington, D.C., from the sample. The regressions are unweighted, whereas in Figure 1 we show a population-weighted fit. SSS employment share is the fraction of local employment in a commuting zone in NAICS industries 51, 52, 54, or 55 (see Eckert, Ganapati, and Walsh, 2020b). College employment share is the fraction of workers with at least a college degree in a given commuting zone. Standard errors are robust and stated in parentheses. *** indicates significance at the 1 percent level, ** indicates significance at the 5 percent level, * indicates significance at the 10 percent level.

II. THE PANDEMIC AND URBAN COMMUTING ZONES

During the pandemic, remote work increased dramatically in the U.S., particularly in its densest commuting zones. The top left panel of Figure 2 uses the cellphone data provided by Couture, Dingel, Green, Handbury, and Williams (2020) to show the cumulative changes in local population, relative to January 2020, by month across commuting zones of different density throughout the pandemic. As the pandemic accelerated in March 2020, U.S. population flowed from the most to the least dense commuting zones. The relocation of population from more to less dense commuting zones was substantial. About 5 percent of workers had left the densest commuting

FIGURE 2: WORK-FROM-HOME AND WORK-FROM-ANYWHERE DURING THE PANDEMIC



Notes: For the first column, we use data provided by Couture, Dingel, Green, Handbury, and Williams (2020) to construct a measure of local population growth relative to January 2020 on the county level. For the second column, we use data provided by Facebook on the fraction of workers in each county who worked from home during the pandemic. To construct groups, we order commuting zones by their population density in 2010 and then split them into ten groups of increasing density, each accounting for about one tenth of the U.S. population in 2010. In the second row of the figure we repeat this exercise but order counties instead by the SSS employment share among their residents.

zones at its peak, and the least dense commuting zones had gained almost 10 percent in local population relative to January 2020.[3]

At the same time, workers who stayed in dense commuting zones began to work-from-home at higher rates than elsewhere (although this had reversed somewhat by the end of 2020).[4] The right panel of Figure 2 uses county-level data on work-from-home

[3] Another paper studying migration responses to the recent pandemic using cell phone data is Coven, Gupta, and Yao (2020). In the Appendix, we recompute the first panel of Figure 2 in another cellphone data set. The results are qualitatively similar, but both positive and negative population growth numbers are more extreme. In the Appendix, we also show that dense locations saw rent price declines, and less dense locations rent price increases, providing further evidence for the patterns of local population growth we document.

[4] The Current Population Survey added questions about work-from-home in May 2020 in response

provided by Facebook to show the fraction of workers working from home throughout different months of the Pandemic.[5] These findings show that the pandemic turned the predicted relationship between commuting zone population density and remote work from Figure 1 into reality.[6] Work-from-home peaked across commuting zones in May, with almost 10 percentage points more workers working from home in the most relative to the least dense commuting zones.

The second row of Figure 2 repeats the first, but across counties ordered by the SSS employment share among its residents. It shows that counties with more SSS workers among their population saw greater out-migration and a greater fraction of workers resorting to working from home. The counties with the largest shares of SSS employment among their residents had seen more than a 5 percent decline in their local populations by the fall of 2020. Counties with few SSS workers, often low-density locations, had seen a more than 5 percent increase in the local population.[7]

Overall, out-migration and work-from-home were biased towards more dense commuting zones, and within them towards counties with disproportionate amounts of high-income, skilled service workers. For these SSS workers, an essential part of what makes dense cities attractive are the opportunities for local service consumption they offer (see Glaeser, Kolko, and Saiz, 2001). Both working from home and working from somewhere else potentially reduce local expenditure on consumer services.[8] As a result, locations with a large fraction of SSS workers experienced a particularly large decline in local consumer service expenditure.[9]

Using cellphone data from SafeGraph, we compute changes in the visits to local consumer service establishments, such as hotels, restaurants, coffee shops, bars, and barbers, for each zip code in the United States. Figure 3 shows the reduction of such visits by SSS employment share among residents (left panel).[10] There is a sharp reduction

to the pandemic. These data show that SSS workers were by far the most likely to actually work-from-home, consumer service workers ("Arts and Hospitality") the least likely, and that bigger cities saw a larger fraction of overall workers work-from-home, reflecting their specialization in SSS industries.

[5]We also recomputed these outcomes using data from Coven et al. (2020) and find patterns that are broadly consistent with these findings.

[6]Taken together Figures 1 and 2 also provide a further validation of the predicted work-from-home measure introduced by Dingel and Neiman (2020).

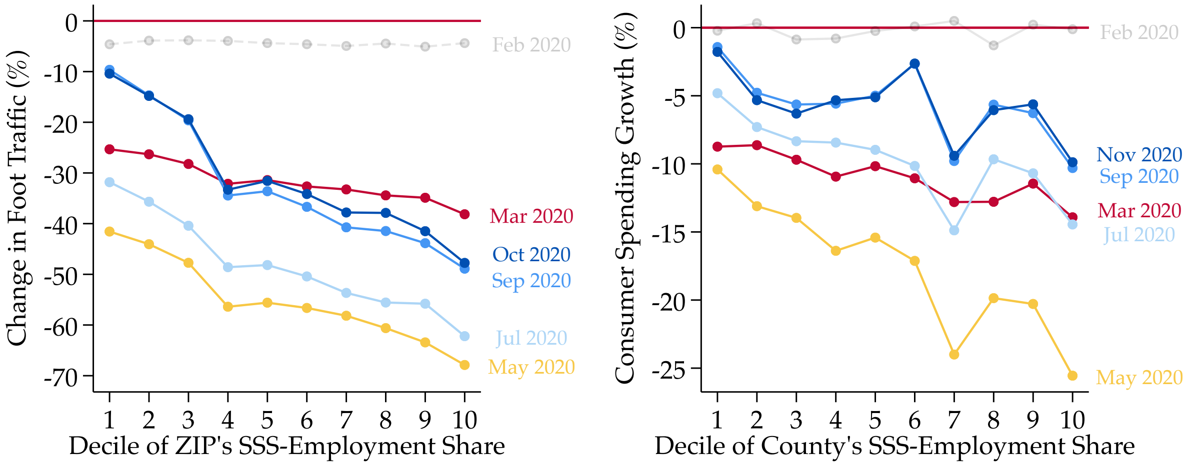
[7]Delventhal and Parkhomenko (2020) and Delventhal, Kwon, and Parkhomenko (2020) provide theoretical models of telecommuting in response to the pandemic whose predictions are consistent with the empirical evidence we provide.

[8]Work-from-home may also change the composition of local expenditure, tilting it from spending on restaurants to local supermarkets.

[9]This accords with the findings by Chetty, Friedman, Hendren, Stepner et al. (2020) that low-skill consumer services workers were hit hardest, particular in the richest zip codes of the United States. We document the mechanism behind these findings: the changes in the geography of consumption of high-skill service workers.

[10]Workers could also spend in the location of their work. In the Appendix, we repeat Figure 3 but instead order zip codes by the fraction of SSS among local *employment*.

FIGURE 3: LOCAL SERVICE CONSUMPTION DURING THE PANDEMIC



Notes: The left panel shows the change in foot traffic to local service establishments across counties relative to January 2020 using data from SafeGraph. The right panel uses data from Chetty et al. (2020) to show changes in consumer spending across counties. Changes are seasonally adjusted and relative to January 4-31, 2020. To construct county groups, we order commuting zones by their SSS employment share in 2010 and then split them into ten groups of increasing density, each accounting for about one-tenth of the U.S. population in 2010.

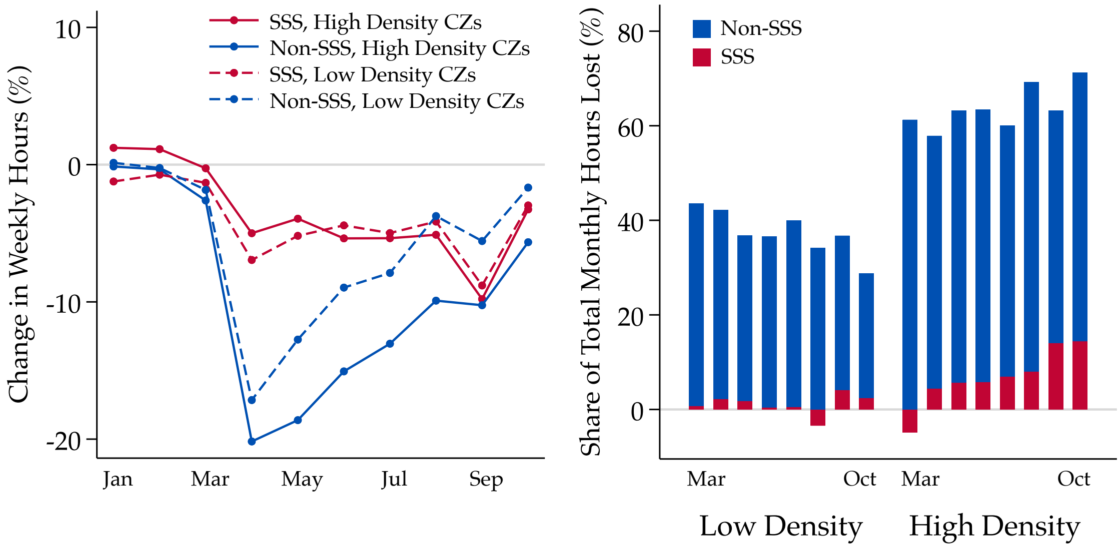
in visits everywhere, but the drop is almost twice as large in zip codes with more SSS workers or residents by the pandemic's peak.

Next, we use data from Chetty, Friedman, Hendren, Stepner et al. (2020) to measure consumer spending on the county level directly. We show the reduction in consumer spending by SSS employment share among residents (left panel) and workers (right panel) in Figure 4. The consumer spending data gives total spending, which is not necessarily local. These data corroborate the evidence from the cellphone data in the left panel: spending on consumer services has declined more in locations home to more SSS workers.

These changes in spending were directly reflected in employment outcomes for low-skill workers. The left panel of Figure 4 uses data from the Current Population Survey (CPS) to plot the decline in hours worked for SSS and non-SSS jobs in commuting zones denser than the median and less dense than the median, month by month throughout the pandemic. Strikingly, SSS workers are similarly affected regardless of where they worked, showing how the ability to work remotely insulates workers from shocks to their local labor market (see Burstein, Hanson, Tian, and Vogel, 2020). Non-SSS workers in big cities, including the consumer service workforce, are hit much harder in the pandemic than their colleagues in less dense commuting zones. The incident of the initial shock for them is more severe, and their recovery markedly slower.

The right panel of Figure 4 shows the fraction of total hours lost relative to January 2020 by location and industry. We split the entire U.S. into the least dense commut-

FIGURE 4: EMPLOYMENT OUTCOMES DURING THE PANDEMIC



Notes: The left panel uses data from the Current Population Survey to show changes in weekly hours worked across commuting zones and industry groups throughout the pandemic. Data is for 2020 and month 1 is January 2020. Changes are measured relative to the average worker in January 2020. The right panel shows the same outcome as a fraction of total monthly hours loss. Dense commuting zones are defined as a commuting zone above the median density.

ing zones accounting for 50 percent of employment ("Low Density") and the densest commuting zones accounting for the other half ("High Density"). We then calculate the total hours lost within each group relative to January 2020 for the SSS and non-SSS sectors separately. As can be seen, despite accounting for the same amount of employment initially, about 60 percent of total hours lost were lost in more dense commuting zones, with the large majority due to non-SSS workers.[11] In November, non-SSS workers in the densest commuting zones accounted for 60 percent of all hours lost. Workers in SSS industries have been faring similarly regardless of location. Non-SSS workers, however, have done significantly worse in dense locations and born the brunt of the pandemic induced decline of consumer service expenditure.

Cities' specialization in SSS work and consumer service industries implies that their low-skill workers are uniquely exposed to remote work shocks. These low-skill workers have seen their urban wage premia eroded in recent decades as more and more of them moved into consumer services in the U.S. densest urban areas (see Autor and Dorn, 2013; Autor, 2019). At the same time, these cities became more expensive to live in due to the SSS industries' success (see Eckert, Ganapati, and Walsh, 2020b). In this paper, we document another vulnerability of low-skill workers: their disproportionate and one-way dependence on SSS workers' local service demand for their livelihood.[12]

[11] The larger loss of hours for SSS workers in high-density commuting zones reflects the higher initial employment shares for SSS in these locations (see Eckert, Ganapati, and Walsh, 2020b)

[12] Almagro and Orane-Hutchinson (2020) and Almagro, Coven, Gupta, and Orane-Hutchinson (2020)

III. Concluding Remarks

We draw two broader lessons from our work. First, with their unique division into remote work and local consumer services, city economies are particularly vulnerable to remote-work shocks such as pandemics. This adds to the already precarious condition of low-skill service workers, which have suffered in recent years from skyrocketing house prices (see Couture, Gaubert, Handbury, and Hurst, 2019) and stagnant wages (see Autor, 2019).

Second, the pandemic has brought the city paradox to the fore. One might imagine two broad explanations for the concentration of high-skill, remote workable service jobs in big cities.

Suppose skilled workers value city living mainly for consumption amenities, choosing to live there despite their ability to work anywhere. Many amenities are effectively scale technologies that need dense cities to be profitable, such as opera houses, large international airports, large museums, niche restaurants, and niche social clubs. In this case, cities may suffer as long as amenity consumption is severely impacted by the pandemic, but would likely recover their old strength once the pandemic is over.

On the other hand, suppose skilled workers receive high wages in big cities due to the unique productive advantages they bestow. The technological developments in telecommunication and the change in norms around remote work ushered in by the recent pandemic may mean that firms discover that there are fewer reasons to be in downtown NYC than they thought. If this occurs, there may be a long-term shift in large cities' dominance in U.S. economic geography.

Either eventuality will yield important insights into the determinants of the spatial disparities between cities in the United States observed today.

have pointed to another set of additional vulnerabilities of low-skill service workers in big cities: that their face-to-face jobs have implied disproportionate contracting of the COVID-19 virus itself.

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Appendix

A. Data Sources and Construction

In this Appendix, we discuss our data sources, data construction, and sample selection. We use the following sources of data.

American Community Survey We use the American Community Survey (ACS) public-use files provided by Ruggles, Sobek, Alexander, Fitch, Goeken, Hall, King, and Ronnander (2015). We use the classification of occupations into those that can be done from home and does which cannot from Dingel and Neiman (2020). We apply their classification to occupations in the ACS data to compute the fraction of jobs and the fraction of payroll in occupations that can be done from home in each commuting zone. We use the commuting zone classification by Tolbert and Sizer (1996) and introduced into the economics literature by Autor and Dorn (2013). We use the crosswalks provided by Autor and Dorn (2013) to map PUMA identifiers in the ACS data to commuting zones. We exclude the states of Alaska, Hawaii, and D.C. and the agricultural and public sectors from our analysis.

Current Population Survey We draw on the Current Population Survey (CPS), a monthly, nationally representative labor market survey conducted by the U.S. Census Bureau and provided by Ruggles et al. (2015).

We use data on weekly hours worked from the 2019-2020 CPS Monthly Basic (CPS-Basic), a survey of approximately 60,000 households in the U.S. Each household is included four consecutive months, then pauses for eight months, and is then included for another consecutive four months. Data on earnings is drawn from the CPS Outgoing Rotation Group (CPS-ORG). The CPS-ORG covers only households in the fourth and eighth sample months and includes additional information not contained in the CPS-Basic, such as earnings.

We exclude the states of Alaska, Hawaii, and D.C. and the agricultural and public sectors from our analysis. While typically around 50,000 households respond to the CPS each month, with the onset of the COVID-19 pandemic, response rates have dropped, reducing the number to around 40,000.[13]

County Business Patterns We use data on zip code level employment counts by industry provided by Acosta et al. (2020). The authors use the County Business Patterns

[13] For a detailed discussion, see https://cps.ipums.org/cps/covid19.shtml.

data provided by the U.S. Census and apply a variation of the technique proposed by Eckert, Fort, Schott, and Yang (2020a) to impute employment counts on the zip code level. We use the 2016 cross-section of the data to construct Skilled Scalable Service employment counts on the zip code level for all zip codes in the US.

Census Transportation Planning Products Database We use data on commuting flows from the Census Transportation Planning Products (CTPP) program by the Department of Transportation. The CTPP data product is based on 2012–2016 5-year ACS Data and designed to help transportation analysts and planners understand where people are commuting to and from, and how they get there. The information is organized by residence, workplace, and commute from home to work. It provides data on commuting flows between all ZIP codes in the US.

We combine the data with the data on employment shares among workers in each zip code from the County Business Patterns to infer employment shares among residents in each zip code. We assume that the sectoral composition among workers commuting from zip code A to B corresponds to the sectoral decomposition among workers working in zip code B which we observe in the County Business Patterns data. We likely underestimate the residential sorting of workers by industry.

DescartesLabs Data We use data on the number of smartphone users residing in each county by Descartes Labs (Warren and Skillman, 2020). The data consists of anonymized, aggregated smartphone movement data. We normalize the monthly count of devices in each county with the monthly growth of devices contained in the national dataset. The normalized monthly growth in devices by county is used as a proxy for population growth. We use this data to validate the migration patterns estimated using PlaceIQ Movement Data.

Facebook Work From Home Data We use county-level data on the fraction of residents who stay at home on a given day from Facebook. Every smartphone user who does not leave their approximately 600 meters by 600 meters large home-tile is classified as somebody who stays at home. Home-tiles are assigned to users based on the location they stay in overnight. We assume that the fraction of people staying at home is a proxy for a fraction of people working from home.

Only users of Facebook's mobile application who opt into location history and background location collection are included. Only people whose location is observed for a meaningful period of the day are used to compute county-wide measures.[14]

[14] For more information on the Facebook data, see https://research.fb.com/blog/2020/06/protecting-privacy-in-facebook-mobility-data-during-the-covid-19-response/

PlaceIQ Movement Data We use data on the number of smartphone users residing in each county by Couture et al. (2020). The data is derived from anonymized, aggregated smartphone movement data provided by PlaceIQ. We normalize the monthly count of devices in each county with the monthly growth of devices contained in the national dataset. The normalized monthly growth in devices by county is used as a proxy for population growth.

We have successfully reproduced the migration patterns using other data sources, such as VenPath (e.g., used in Coven et al., 2020) and DescartesLabs.

SafeGraph Data We use data on foot traffic by commercial point of interest (POI) from SafeGraph. Each commercial POI corresponds to one of around six million unique business locations in the U.S. SafeGraph provides the number of smartphone users that each POI is visited by throughout the day. We use information on a business's industry to limit our analysis to consumer POIs. We then aggregate the total number of visits to the industry-by-ZIP code level. We normalize the number of visits by the total number of devices observed in the SafeGraph dataset in each month.

SafeGraph collects geolocation data from smartphone users though specific apps. The data used in this paper is anonymized.

Track the Recovery Data We use data on daily consumer spending by county from Affinity Solutions, provided by Chetty et al. (2020). The data consists of aggregated and anonymized purchase data from consumer credit and debit card spending. Spending is reported based on the ZIP code where the cardholder lives, not the ZIP code where transactions occurred. We use the 7-day moving average of seasonally adjusted credit/debit card spending relative to January 4-31, 2020 in all merchant categories.[15]

Zillow Data We use monthly data on ZIP-level average rental apartment prices. The Zillow Observed Rent Index (ZORI) is a smoothed measure of the typically observed market rate rent across ZIP codes. It is weighted to the rental housing stock to ensure representativeness across the entire market. Only listed rents that fall into the 40th to 60th percentile range for all homes and apartments in a given region are included.[16]

We compute the average change in the ZORI over January 2020 across all ZIP codes within a county. We then substract the monthly national average change in the ZORI,

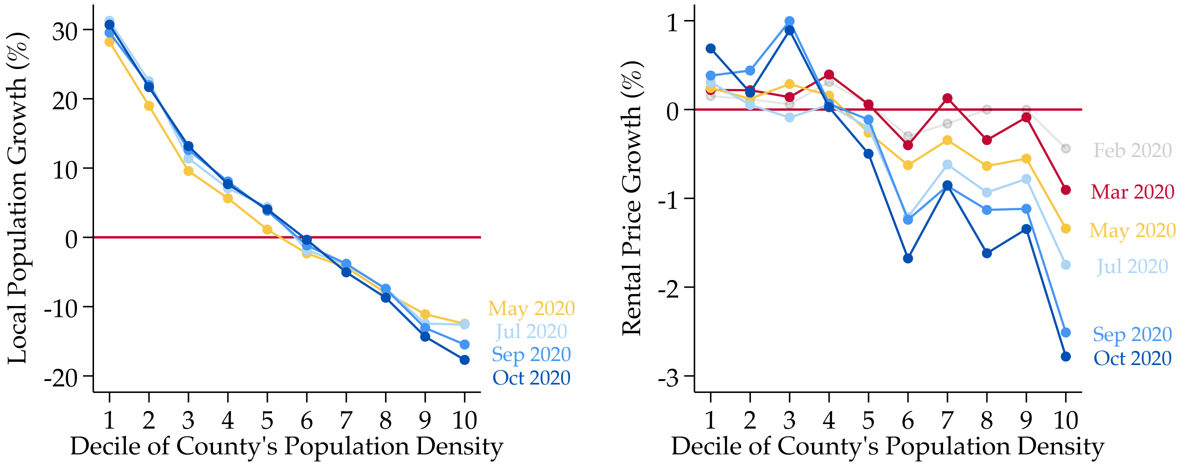
[15] "The Economic Impacts of COVID-19: Evidence from a New Public Database Built Using Private Sector Data", by Raj Chetty, John Friedman, Nathaniel Hendren, Michael Stepner, and the Opportunity Insights Team. November 2020. Available at: https://opportunityinsights.org/wp-content/uploads/2020/05/tracker_paper.pdf

[16] For more details on the methodology employed by Zillow, see https://www.zillow.com/research/methodology-zori-repeat-rent-27092/.

i.e., the unweighted average increase over all counties, from each county's change. To reduce the impact of outliers, we drop the lowest and highest two percentiles of counties in terms of price growth.

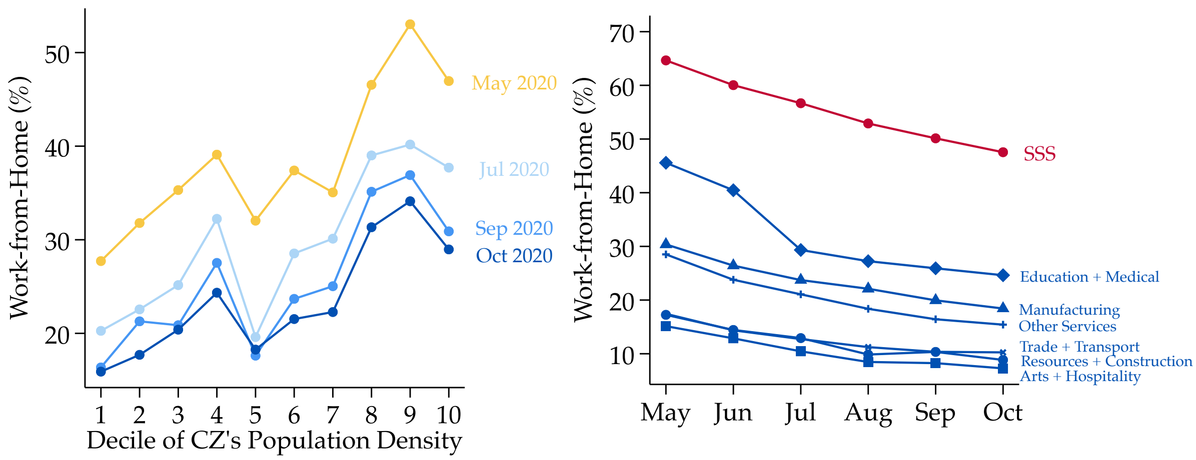
B. Additional Figures

Figure B.1: Local Population Growth and Rental Home Prices



Notes: For the left panel, we use data provided by DescartesLabs to construct a measure of local population growth relative to March 2020 (the first month for which data is available) on the county level. For the right panel, we use data provided by Zillow on the price growth among rental homes. The series displayed is the change in average rental prices in each county net of the national average of price changes. To construct groups, we order counties by their population density in 2010 and then split them into ten groups of increasing density, each accounting for about one tenth of the US population in 2010.

Figure B.2: Work from Home During the Pandemic



Notes: We use data on the fraction of people working from home in each industry from the CPS's supplemental COVID-19 measures. The variable "covidtelew," reflects whether or not a person has done telework or work-from-home in the last four weeks because of the COVID-19 pandemic. To construct groups in the left panel, we order counties by their population density in 2010 and then split them into ten groups of increasing density, each accounting for about one tenth of the US population in 2010.