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# THE GEOGRAPHY OF REMOTE WORK

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## ABSTRACT

We show that cities with higher population density specialize in high-skill service jobs that can be done remotely. The urban and industry bias of remote work potential shaped the COVID-19 pandemic's economic impact. Many high-skill service workers started to work remotely, withdrawing spending from big-city consumer service industries dependent on their demand. As a result, low-skill service workers in big cities bore most of the recent pandemic's economic impact. Our findings have broader implications for the distributional consequences of the U.S. economy's transition to more remote work.

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# INTRODUCTION

The most populated cities in the United States specialize in producing skill- and information-intensive services (see Eckert, Ganapati, and Walsh, 2020). As a result, many of these cities' residents work in high-skill service industries. In addition, high-skill service workers' expenditure on non-tradable consumer services, such as restaurants and hairdressers, sustains a large class of low-skill service workers in these cities (see Glaeser, Kolko, and Saiz, 2001).

As technology and high-speed internet have become more accessible, a disproportionate fraction of these high-skill service jobs has acquired the potential to be done remotely. As a result, the specialization of big cities in high-skill services has translated into a specialization in remote work jobs. However, until recently cities' elevated potential for remote work was inconsequential since the vast majority of workers did not make use of it (see Bloom, Liang, Roberts, and Ying, 2015).

The pandemic forced much of the U.S. economy to transition to remote work within weeks. We use this episode as a case study for two related ends. First, we show that the relationship between population density and remote work potential translated into a relationship between population density and actual remote work during the pandemic. This suggests city-level remote work potential is a good measure for the exposure to the rise of actual remote work in the U.S. economy. Second, we trace out one important implication of big cities' specialization in remote work that was very evident during the pandemic.

The urban- and industry-bias of the rise in remote work has shaped the economic impact of the pandemic. Within cities, neighborhoods with more high-skill service residents saw larger population outflows and higher work-from-home numbers throughout the pandemic. High-skill service workers' flight into their homes and to locations outside big, dense cities had adverse consequences for the urban economies they left behind. The larger a neighborhood's initial share of high-skill service workers among its residents, the larger its decline in visits to local consumer service establishments and the sharper the drop in residents' spending on consumer services. The low-skill service workers in these neighborhoods suffered from this change in consumption behavior: low-skill consumer service workers in big cities lost more hours per worker than their rural counterparts and have been most affected by the pandemic's economic fallout.

Our findings highlight the one-way dependence of non-tradable service workers on the local spending of workers in high-wage tradable industries and have implications for the transition to remote work more generally. For the longest time, workplace proximity was central to workers' residential decisions, keeping them in big cities despite high living costs. However, the transition to more remote work will affect regions and workers differently depending on their remote work potential. If the recent pandemic is any guide, high-skill service workers will benefit from increased spatial flexibility and make use of it, while low-skill service workers will suffer from their dependence on local demand in a more footloose world.

Big cities themselves face a dual threat: they may lose not only their increasingly footloose high-skill workers but also the local consumer service economies these workers support. As a result, they may shrink in size unless they manage to provide advantages that justify the costs of urban density when residential choices are set free from proximity-to-workplace considerations.

## I. The Geography of Remote Work Potential

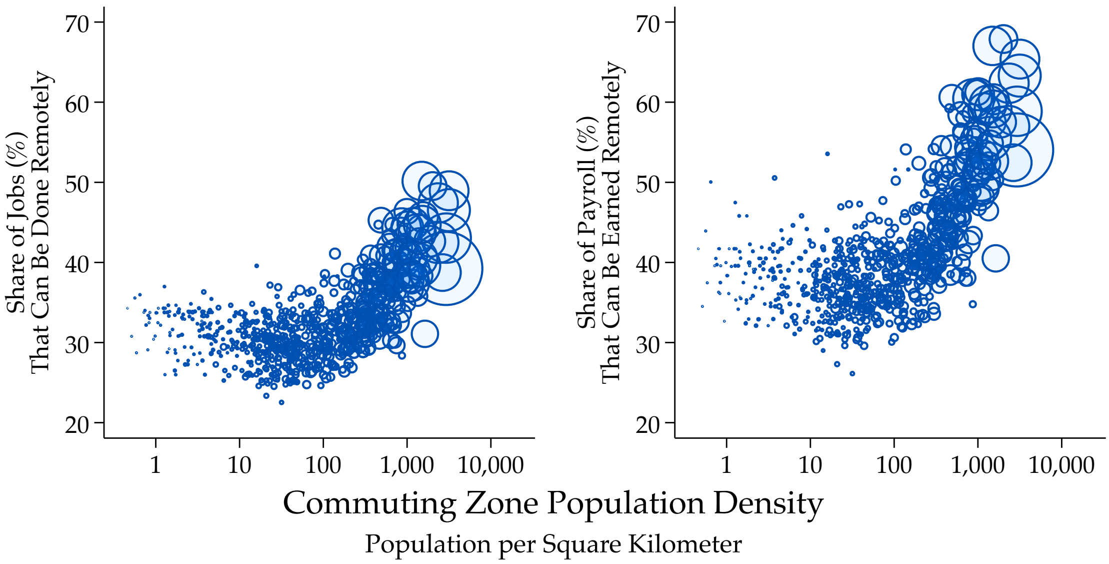
We start by documenting that cities' remote work potential increases in population density. We use the occupation-based work-from-home classification introduced by Dingel and Neiman (2020) and match it to data on occupational employment shares in all U.S. commuting zones.[1] The left panel of Figure 1 plots the share of jobs that can be done remotely against commuting zone population density.[2] The relationship is striking: the higher a city's population density, the greater its potential for remote work. In America's densest cities, around 45 percent of local jobs have the potential to be done remotely, corresponding to about 65 percent of the local payroll. The difference between the remote work potential in terms of jobs and payroll reveals that jobs that can be done from anywhere also pay higher wages on average.

The elevated remote work potential of dense cities originates from their industrial structure. Eckert, Ganapati, and Walsh (2020) show that dense U.S. cities specialize in the production of a set of skill- and information-intensive services, dubbed "Skilled Scalable Services" (SSS): Information (NAICS 51), Finance and Insurance (NAICS 52), Professional Services (NAICS 54), and Management of Companies (NAICS 55). The SSS industries' intensive and increasing use of information and communications technology explains their high potential for remote work. In Table A.1 in the Appendix, we show the fraction of jobs within each industry that can be done remotely. The share of jobs with remote work potential in SSS is 79%, substantially higher than that of any other industry.

[1] We use the five-year American Community Survey files for 2014-2018.

[2] Following Glaeser and Kahn (2004), we compute the population density of a commuting zone as a population-weighted average of the population density of its ZIP Codes to take into account the spatial distribution of residents *within* them.

FIGURE 1: REMOTE WORK POTENTIAL ACROSS CITIES




*Notes*: We use occupation-level employment data from the pooled American Community Survey from 2014-2018. We use the occupation-specific "work-at-home" classification by Dingel and Neiman (2020). The figure also shows the fitted line of a population-weighted OLS regression. To derive commuting zone population density, we follow Glaeser and Kahn (2004) in computing the population-weighted average of the population density across commuting zones' ZIP codes. We use ZIP code total population from the 2015-2019 American Community Survey. The sample contains 722 commuting zones as defined by Tolbert and Sizer (1996) covering the entire territory of the states in the sample. We drop data for Alaska, Hawaii, and Washington, D.C., from our sample.

TABLE 1: REMOTE WORK POTENTIAL AND INDUSTRIAL STRUCTURE

| | Share of Jobs That Can Be Done Remotely | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Log Population Density | 0.010*** | 0.001*** | 0.002*** | 0.000 | 0.001 |
| | (0.001) | (0.001) | (0.000) | (0.000) | (0.002) |
| SSS Employment Share | | 1.293*** | | 0.645*** | 1.263*** |
| | | (0.039) | | (0.059) | (0.158) |
| Log Population Density $\times$ | | | | | 0.005 |
| SSS Employment Share | | | | | (0.024) |
| College Employment Share | | | | 0.391*** | |
| | | | | (0.033) | |
| NAICS2 Employment Shares | No | No | Yes | No | No |
| Adjusted R-squared | 0.215 | 0.798 | 0.915 | 0.887 | 0.797 |
| Observations | 722 | 722 | 722 | 722 | 722 |

*Notes*: We use occupation-level employment data from the pooled American Community Survey from 2014-2018. We classify workers according to the occupation-specific "work-from-home" measure by Dingel and Neiman (2020). The table shows the output of five regressions run for 722 commuting zones (see Tolbert and Sizer, 1996) covering the entire territory of the United States. We drop Hawaii, Alaska, and Washington, D.C., from the sample. 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, 2020). College employment share is the fraction of workers with at least a college degree in a given commuting zone. To derive commuting zone population density, we follow Glaeser and Kahn (2004) in computing the population-weighted average of the population density across commuting zones' ZIP Codes. We use ZIP Code total population from the 2015-2019 American Community Survey. Robust standard errors are stated in parentheses. *** significant at the 1 percent level, ** significant at the 5 percent level, * significant at the 10 percent level.

Table 1 demonstrates that these four industries alone almost entirely account for the elevated remote work potential of denser cities. Column 1 quantifies the relationship between commuting zone density and remote work potential. This relationship becomes an order of magnitude weaker once we control for the local SSS employment share (Column 2). Furthermore, the R-squared rises from 0.2 to 0.8: most of big cities' remote work potential is accounted for by their specialization in SSS industries. Column 3 shows that controlling for the employment share of all 2-digit NAICS industries (among them the SSS industries) does not substantially improve the regression fit: variation in cities' industrial structure beyond SSS does not help explain the cross-city variation in remote work potential. The fraction of college workers in the local labor force also adds little explanatory power (see Column 4). Including the college share lowers the coefficient on the SSS employment share somewhat, reflecting the fact that SSS industries are skill-intensive by construction. In Column 5, we separately interact the local SSS employment share with local population density. The coefficient on the interaction term is small and insignificant. Since the underlying remote work measure by Dingel and Neiman (2020) is based on occupations, this suggests that the composition of occupations within SSS industries is similar across cities of different population density.[3]

In summary, we find that the higher a city' population density, the higher the fraction of its workforce that could theoretically work remotely. Worker in jobs with remote work potential earn above-average incomes and work largely in high-skill service industries. The prevalence of high skill service workers in big cities is the chief driving force behind the strong positive relationship between remote work potential and city population density. Our findings are important since they suggest that cities of different size and workers in different industries differ in their exposure to changes that lead to more remote work in the U.S. economy.

## II. THE GEOGRAPHY OF ACTUAL REMOTE WORK

Since until recently only 2.4 percent of Americans worked remotely – less than 1-in-15 of the 37 percent who could do so in theory – the remote work potential of big cities had no tangible impact on city economies (see Mateyka, Rapino, and Landivar, 2012; Dingel and Neiman, 2020). However, the recent pandemic drastically lowered the relative cost of remote work and led large parts of the U.S. economy to start working remotely almost overnight (see Bartik, Bertrand, Cullen, Glaeser, Luca, and Stanton, 2020; Bick, Blandin, and Mertens, 2020).[4] We show that in line with our findings on the geography of remote work potential, big cities saw much larger fractions of their workforce move to remote work during the pandemic compared to smaller cities.

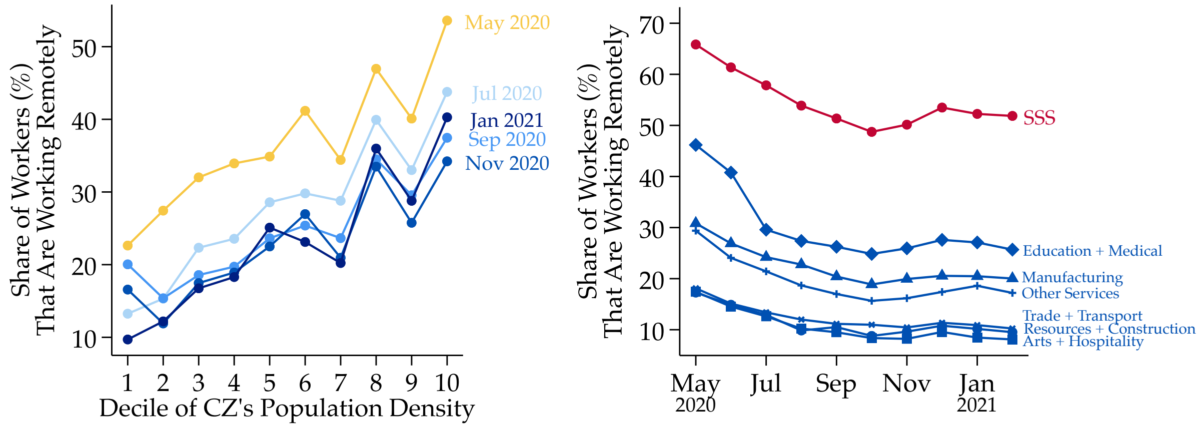
In May 2020, the U.S. Current Population Survey (CPS) began to include monthly questions about remote work. The CPS reported a remote work rate of about 40 percent for May 2020, in line with numbers from others surveys (see, e.g., Bick et al., 2020).[5] A convenient feature of the CPS is the breadth of other individual-level infor-

[3]In other words, occupational composition is almost completely accounted for by variation in industrial composition. The within-industry spatial variation in occupations (at least in terms of scope for remote work) is very small.

[4]Glaeser, Gorback, and Redding (2020) show that commuting to work substantially increased workers' risk of contracting COVID-19.

[5]Bick et al. (2020) report about 31% of workers working remotely in May, with an additional 13% working remotely part of the week. Brynjolfsson, Horton, Ozimek, Rock, Sharma, and TuYe (2020) report a number of 50% of workers working from home early on in the pandemic. The CPS reports the following percentages of remote work from May through to December: 40%, 36%, 32%, 28%, 27%, 25%, 25%, and 28%.

FIGURE 2: REMOTE WORK DURING THE PANDEMIC




*Notes*: We use data on the fraction of people working remotely 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. In the left panel, we order commuting zones by their population density and then split them into ten groups of increasing density, each accounting for about one tenth of the U.S. population. To derive commuting zone population density, we follow Glaeser and Kahn (2004) in computing the population-weighted average of the population density across commuting zones' ZIP Codes. We use ZIP Code total population from the 2015-2019 American Community Survey. We drop data for Alaska, Hawaii, and Washington, D.C., from our sample.

mation contained in the data set, such as the location of residence and the industry of the respondent.[6]

We use the CPS data to document the importance of remote work across cities and industries during the pandemic. We group commuting zones into ten bins of increasing density, each accounting for 10 percent of the U.S. population.[7] The left panel of Figure 2 shows the fraction of workers who worked remotely in various months of the pandemic for each of these ten commuting zone bins. In May 2020, more than 50 percent of workers in the densest cities worked remotely, compared to only slightly above 20 percent of workers in the least dense cities. The range of actual remote work shares is very close to that of the potential remote work shares shown in the left panel of Figure 1. Figure 2 shows that the pandemic-induced rise in remote work was strikingly density-biased.

The right panel of Figure 2 shows the fraction of workers doing remote work across industries. The fraction of SSS workers doing remote work is more than twice as high

[6] The location of residence is recorded in the first interview. Since the CPS operates in waves, most of the respondents in the survey registered with their pre-pandemic address. We explain below how pandemic-induced migration of CPS respondents affects our statistics.

[7] We follow Glaeser and Kahn (2004) in computing the population-weighted average of the population density of the ZIP Codes contained in a given commuting zone to derive commuting zone population density numbers. We use ZIP Code total population numbers from the 2015-2019 American Community Survey files.

as that of the rest of the U.S. economy. At the same time, the SSS employment share in the densest cities is more than double that of the least dense cities (see Figure A.2 in the Appendix).

The findings in this section suggests that big cities were indeed more exposed to the rise in remote work during the pandemic than smaller ones, in line with our findings on the geography of remote work potential in the previous section. As a result, large cities are also likely to be more exposed to the broader transition of the U.S. economy to more remote work in the aftermath of the COVID-19 pandemic, at least initially.

## III. The Impact of Remote Work on Local Service Workers

In this section, we highlight an important implication of the geography of remote work potential and its underlying industrial origins. Big city economies are divided into high-skill service workers in jobs with high remote work potential and low-skill consumer service workers without such potential. As the high-skill workers transition to remote work they may choose to leave expensive cities, or consume more at home, reducing the demand for local consumer service offerings. We use the recent pandemic to provide evidence for the importance of this mechanism.

Our basic research design is to study whether a larger fraction of high-skill services workers, so-called "SSS workers," among the residents of a given city neighborhood prior to the pandemic predicts population outflows and declines in local consumer service spending during the pandemic. A challenge is that urban density itself played a significant role in the propagation of the COVID-19 epidemic: larger cities were hit earliest and hardest (see Carozzi, Provenzano, and Roth, 2020; Coven, Gupta, and Yao, 2020). In response, many of these cities imposed lock-downs that forced workers to work remotely and consumer service establishments to close. Since population density and SSS employment shares are highly correlated in the cross-section of cities, such policies create a correlation between SSS employment shares, the rise of remote work, and declines in consumer service demand across cities. Fortunately, the high-resolution spatial data available for the U.S. allows us to focus on variation across neighborhoods within cities, where both policy and disease dynamics are likely to be similar to a first-order. Consequently, we define all outcome variables at the ZIP code or county level and control for city-level policies and disease dynamics using month-city fixed effects.

First, we show that within a given city, the more a ZIP code's residents work in SSS, the higher the losses in population and the larger the increase in work-from-home. We use cellphone data from SafeGraph to study a ZIP code's changes in local population relative to January 2020. The first column of Table 2 shows that ZIP codes with a larger SSS employment share among their residents saw larger population outflows, with the cumulative effect peaking in April 2020.[8] We repeated the analysis with a different cell-phone-based data set from Couture, Dingel, Green, Handbury, and Williams (2020) on the county level in Column 2 and find broadly consistent results. We control for commuting-zone-month fixed effects and use only within commuting zone and month variation to identify these effects.

In Figure A.2 in the Appendix, we also graph commuting zones' population growth against their population density: the rise of remote work led to a distinct reallocation of workers from high- to low-density commuting zones. High-density commuting zones had seen almost a 10 percent decline in their local population by the fall of 2020, whereas low-density commuting zones had seen a more than 5 percent increase in the local population.[9] Together with the regression in Column 1 of Table 2, this suggests that SSS workers were making use of their ability to work remotely.[10]

Data on housing rents from Zillow suggests that at least some of these SSS workers had not just temporarily relocated, but given up on their city residences altogether. Column 3 of Table 2 shows the impact of the outflow of SSS workers on the local rental market. The higher the local SSS share among residents, the larger the decline in rental prices. The decline in rental prices continued throughout the entire year and into January 2021, in line with the population outflow data (see Figure A.1 in the Appendix).[11]

Ramani and Bloom (2021) find that workers moved from more dense to less dense, more remote ZIP codes within Metropolitan Statistical Areas (MSAs) using USPS data on individuals' registered home addresses. Our findings of large outflows of dense ZIP codes (and dense commuting zones) are consistent with their findings. Two factors contribute to the rate of cross commuting zone migration being larger in our data than theirs. First, the commuting zones used in our paper are smaller than MSAs, e.g., the New York MSA contains two commuting zones, one of which is much less dense than the other. As a result, some of the relocation we observe across commuting zones occurs within their MSAs. Second, our cell-phone data also captures temporary moves, while the USPS data only captures permanent moves which individuals

[8]Employment shares are expressed as fractions, i.e., they bounded between zero and one.

[9]Davis, Ghent, and Gregory (2021), 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.

[10]Liu and Su (2020) provide a more comprehensive analysis of the effect of COVID-19-induced migration on housing prices throughout the United States. Cho, Lee, and Winters (2020) document early evidence that employment effects of the pandemic are much larger in larger MSAs.

[11]Garcia, Rosenthal, and Strange (2021) provide similar results for commercial rents.

register with the Postal Service.

Next, we show that SSS workers that did not leave their city disproportionately stayed at home and limited their mobility to small areas around their residence. We consider a measure for staying at home provided by Facebook that is available at the county-day level. It classifies someone as staying at home if they are not observed leaving an area of approximately $600 \times 600$ meter around their home address on a given day. We compute a county-level measure that captures the monthly average likelihood of workers staying at home on a weekday. The "home" address is assigned to users based on the location they usually stay in overnight.[12] The fourth column of Table 2 shows the increase in staying from home relative to March 2020 as a function of the initial SSS employment share among residents. It shows that staying at home increased particularly strongly in counties with a larger SSS share among residents; suggesting that those SSS workers that did not leave the city altogether started to work from home.

Overall, within cities, out-migration and work-from-home were biased towards ZIP codes and 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 et al., 2001). Both working from home and working from somewhere else potentially reduces their local expenditure on consumer services.[13]

We document the effect of SSS workers' departure on the local economies of their resident ZIP codes. 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.[14] The changes in such visits serves as a proxy measure for the demand for local services in these ZIP codes in a given month. The fifth column of Table 2 shows the decline in visits to these establishments in each ZIP Code as a function of the SSS employment share among its residents. The decline in foot traffic into local service establishments tracks the population change and remote work data closely. Within cities, ZIP codes with a larger share of SSS residents saw their local consumer services spending decline more sharply.[15] Of course, workers do not only consumer local consumer service in their

[12]The Facebook measure could be interpreted as work-from-home measure if non-employed and employed Facebook users behave similarly and people working from home are limiting their out-of-home activities like shopping to a 600 meters by 600 meters area around their home.

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

[14]See the Appendix for the full list of establishment types we label consumer services in the SafeGraph data.

[15]This accords with the findings by Chetty, Friedman, Hendren, and Stepner (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

ZIP code of residence.[16] In Appendix Table A.3, we replicate the regression in Column 5 of Table 2 but interact the month with the SSS employment share among *workers* in each ZIP code. As expected, we find a qualitatively similar but less strong effect consistent with evidence that much of workers' consumption takes place around their homes (see Davis et al. (2019)).

Data from Chetty, Friedman, Hendren, and Stepner (2020) further allows us to measure consumer spending on the county level directly, in addition to using store visits as a proxy. The consumer spending data provides total spending on consumer services by the residents of a given ZIP code.[17] Column 6 of Table 2 shows the decline in consumer spending in each ZIP Code as a function of the SSS employment share among its residents. These results corroborate the evidence from the cellphone data in Column 5: spending on consumer services declined significantly more in locations home to more SSS workers.

In the Appendix, we provide various tests for the assumption underlying our research design. Our research design that relies on month-city fixed effects to control for cross-city differences in COVID incidence and on incidence and policies not varying within cities. We further validate this assumption by replicating the regression in Table 2 while directly controlling for COVID cases per capita in each county and month. Table A.4 in the Appendix shows that controlling directly for highly localized COVID incidence leaves our estimates unchanged, suggesting they are not driven by, for example, higher incidence in ZIP codes in which more SSS workers reside. Unfortunately, we do not have data on COVID cases on the ZIP code level. However, we use a proxy measure for the spread of COVID, population density, which is available on the sub-county level. In Table A.5, we repeat the regressions in Table 2 but control for local population density on the ZIP code or county (depending on the regression). Doing so has a negligible effect on the regression coefficient estimates. Finally, as a robustness check, we show that our findings are not driven by the commuting zones in the top decile of population densities. We repeat the analysis in Table 2 on a sample that excludes New York City and San Francisco and find similar results.[18]

The estimates in Table 2 are of an economically meaningful size. As an example, consider the fifth column with visits to consumer service establishments. Figure 3 shows

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high-skill service workers.

[16] Work by Davis, Dingel, Monras, and Morales (2019) and others suggests that location of residence is an important determinant of the location of consumption of consumer services such as restaurants.

[17] The spending is not necessarily only local in nature: workers may also spend around their workplace and in other venues in the city. We only observe these data by ZIP code of residence and can hence not analyse the effect of the pandemic on spending around work locations of workers.

[18] The top density decile in Figure 2 consists of New York and San Francisco only, since together they account for 10 percent of U.S. employment. Our regression in the Appendix highlight that the relationship between work-from-home and density is similarly strong when they are excluded.

a map of New York City's ZIP codes. Each ZIP code is colored according to the decline in visits to consumer service establishments between January 2020 and April 2020 implied by the SSS share among local residents combined with our estimates from Table 2. For comparison, the NYC commuting zone fixed effect for the month of April 2020 is $-38\%$, which is the decline in consumer service visits in a New York City ZIP code with no SSS workers among their residents relative to some reference commuting zone. Affluent areas in Manhattan and Brooklyn, home to many SSS workers, saw declines in visits to local consumer service establishments decline by twice as much than ZIP codes in parts of the Bronx and Brooklyn with less SSS workers among their residents. Consumer service establishments in a hypothetical NYC ZIP code without SSS residents would have seen a decline in visits of about 38% in April whereas those in, say, the Upper West Side would have seen a decline of at least 80% due to the many SSS workers among its residents.

We provide additional evidence for the importance of our mechanism using data from Consumer Population Survey (CPS). The CPS provides a more direct measure for the labor demand for consumer service workers across cities: weekly hours worked for each worker in the survey. Unfortunately, the CPS data is not available for counties or ZIP codes, so that we cannot include it in our analysis in Table 2 directly. Since we cannot exploit within-city variation in the CPS data our evidence here is more suggestive.

The left panel of Figure 4 shows the decline in hours in SSS and non-SSS jobs in high- and low-density commuting zones. We define dense commuting zones as the most dense commuting zones that can jointly account for 50% of U.S. employment in 2015. Strikingly, SSS workers were 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). The pandemic presented a much more severe shock to the hours of non-SSS workers, including consumer service workers. Most importantly, however, non-SSS workers in big cities are much harder hit than their counterparts in small cities, unlike SSS workers.

Together with the evidence in Table 2 the left panel of Figure 4 suggests that consumer service workers in big cities see a larger demand shock than their small city counterparts. The fact that the average SSS workers sees the same decline in hours in both types of cities suggests that the economic shock was similar across cities. However, SSS workers account for a much larger share of big city employment (see Figure A.2 in the Appendix). Figure 4 is not establishing a causal relationship but supports the narrative of our paper.

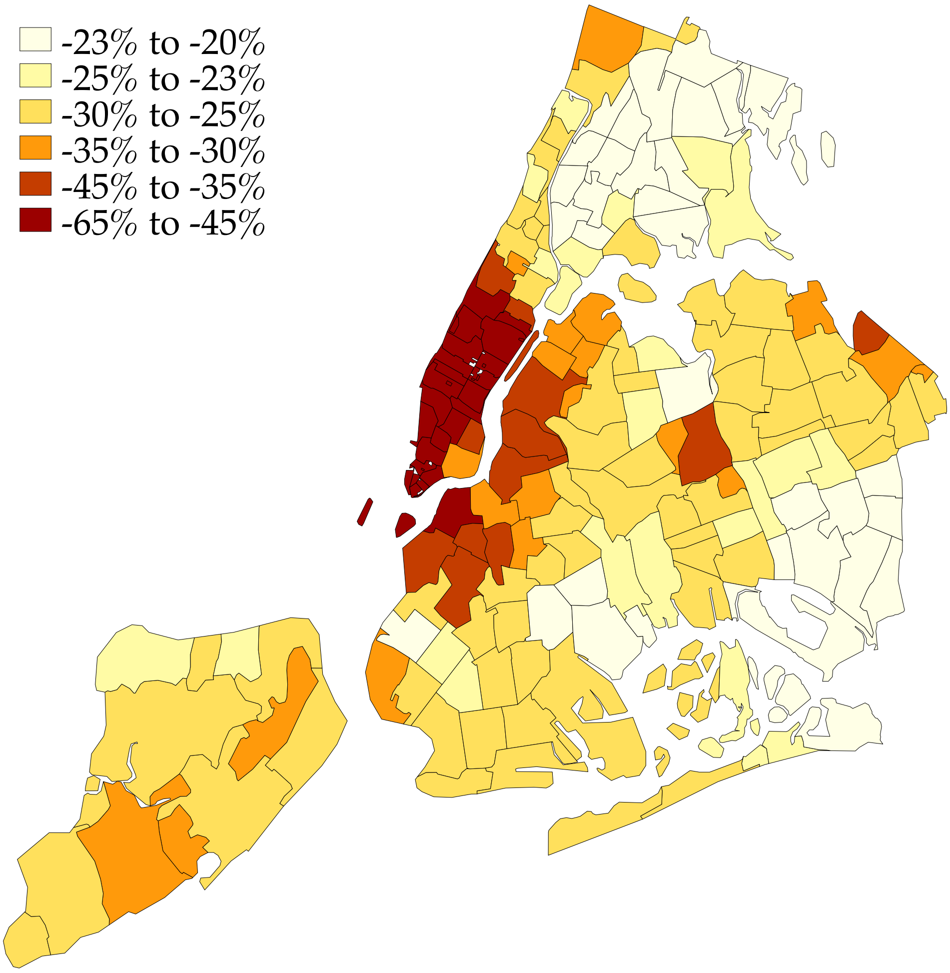
The right panel of Figure 4 provides further evidence that the difference between non-SSS workers economic fate in big and small cities is related to differences in the decline

## TABLE 2: THE IMPACT OF THE REMOTE WORK SHOCK ON CITY NEIGHBORHOODS

| | Growth in | | | | | |
|---|---|---|---|---|---|---|
| | Population (SafeGraph) | Population (PlaceIQ) | Rental Prices (Zillow) | Stay at Home (Facebook) | Foot Traffic (SafeGraph) | Consumer Spending (Affinity) |
| SSS Employment Share × | | | | | | |
| February 2020 | -8.946** | -4.139 | -3.537*** | | -21.681** | 5.795 |
| | (3.789) | (3.772) | (0.230) | | (8.482) | (7.397) |
| March 2020 | -3.914 | -43.710** | -7.071*** | 390.778*** | -82.358*** | -30.327*** |
| | (3.926) | (19.720) | (0.468) | (62.414) | (5.448) | (8.100) |
| April 2020 | -65.666*** | -105.953*** | -10.556*** | 479.789*** | -130.011*** | -100.673*** |
| | (7.614) | (38.173) | (0.700) | (90.672) | (7.114) | (11.475) |
| May 2020 | -49.461*** | -105.413*** | -15.150*** | 390.078*** | -127.518*** | -115.027*** |
| | (8.536) | (37.943) | (1.024) | (58.713) | (8.288) | (14.630) |
| June 2020 | -47.795*** | -88.685** | -19.614*** | 283.027*** | -99.390*** | -101.224*** |
| | (9.015) | (36.590) | (1.353) | (36.200) | (9.130) | (18.568) |
| July 2020 | -40.071*** | -101.798*** | -23.814*** | 234.914*** | -98.380*** | -90.798*** |
| | (10.093) | (32.314) | (1.616) | (28.516) | (10.939) | (18.902) |
| August 2020 | -27.554*** | -98.533*** | -28.475*** | 214.640*** | -84.526*** | -85.909*** |
| | (8.600) | (28.418) | (2.009) | (26.723) | (9.674) | (14.591) |
| September 2020 | -17.438** | -84.663*** | -33.057*** | 208.868*** | -82.440*** | -83.666*** |
| | (7.418) | (21.231) | (2.324) | (28.186) | (10.426) | (22.243) |
| October 2020 | -11.479* | -64.899*** | -37.232*** | 190.658*** | -72.913*** | -80.973*** |
| | (6.127) | (20.941) | (2.715) | (26.100) | (8.070) | (24.349) |
| November 2020 | 2.111 | -85.245*** | -41.635*** | 190.961*** | -69.763*** | -73.068*** |
| | (4.658) | (23.659) | (3.026) | (24.430) | (12.551) | (21.309) |
| December 2020 | -2.295 | -97.806*** | -46.337*** | 206.558*** | -64.811*** | -58.523*** |
| | (5.383) | (23.109) | (3.264) | (28.213) | (9.093) | (17.092) |
| January 2021 | 3.388 | -99.371*** | -51.841*** | 225.669*** | -78.697*** | -102.045*** |
| | (5.742) | (21.392) | (3.589) | (28.795) | (7.191) | (31.390) |
| CZ×Month-FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted R-squared | 0.239 | 0.477 | 0.609 | 0.940 | 0.136 | 0.700 |
| Level of Observation | ZIP | County | ZIP | County | ZIP | County |
| Observations | 479,427 | 26,078 | 32,428 | 29,287 | 421,253 | 20,540 |

*Notes*: We combine the data sets of SafeGraph, PlaceIQ, Zillow, Facebook, and Affinity to measure local outcomes at the ZIP- or county-level (see Appendix A). The dependent variable of all regressions is each outcome's monthly percent growth over its January 2020 baseline (February 2020 if the data is unavailable prior to that). We present estimates on the interaction of the local SSS employment shares and time dummies. All regressions are population-weighted and control for commuting zone × time fixed effects. 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, 2020). We use ZIP Code total population from the 2015-2019 American Community Survey. We drop data for Alaska, Hawaii, and Washington, D.C., from our sample. Standard errors are clustered at the commuting zone-level and stated in parentheses. *** significant at the 1 percent level, ** significant at the 5 percent level, * significant at the 10 percent level.

FIGURE 3: SSS RESIDENTS AND THE DECLINE IN CONSUMER SPENDING IN NEW YORK CITY

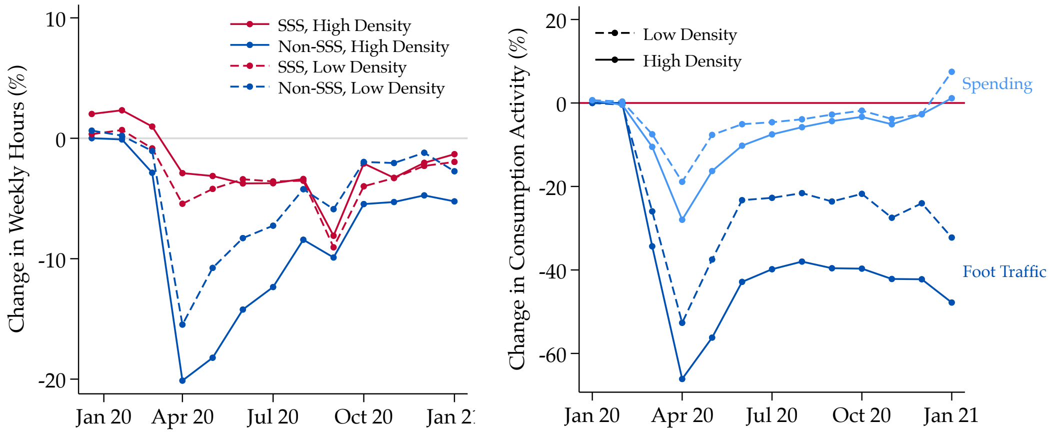



*Notes*: The Figure shows the decline in consumer service establishment visits across New York City ZIP codes in April 2020 relative to January 2020 as predicted by the share of SSS workers among the ZIP codes' residents combined with the estimated coefficients from Table 2. The commuting zone-month fixed effect for April is implies a 38% decline in visits to consumer service establishments in the NYC commuting zone relative to January 2020, compared to some reference commuting zone, for a ZIP code without any SSS workers among its residents.

of consumer service demand between big and small cities. The figure shows the time series of expenditure on consumer services and visits ("foot traffic") to consumer service establishments in big and small cities. Both time series show a steep decline between March and April and then show a recovery that is slower in big cities. The two time series follow that for non-SSS losses in weekly hours remarkably well. Alongside the evidence in Table 2 this suggests that demand for consumer service declined more in big cities as the SSS workers that account for a large part of local consumption changed their consumption habits or worked from elsewhere.

The CPS data also reveals that by January 2021, non-SSS workers in the densest commuting zones accounted for almost 60 percent of all hours lost in the U.S. economy in

FIGURE 4: EMPLOYMENT OUTCOMES DURING THE PANDEMIC




*Notes*: The data on hours worked by industry comes from the Current Population Survey. 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, 2020). The left panel shows changes in weekly hours worked across high- and low-density metropolitan areas and industry groups throughout the pandemic. Changes are measured relative to the average worker in January 2020. The right panel shows the time series of foot traffic into local consumer service establishment relative to January 2020 using the SafeGraph foot traffic data. The right panel also shows the time series of consumer spending relative to January 2020 using the Affinity data. Dense locations are defined as metropolitan areas above-median population density as well as unidentified places in states where commuting zones with above-median density do not exist. We drop data for Alaska, Hawaii, and Washington, D.C., from our sample.

that month relative to the previous year. At the same time these workers accounted for only around 41.1% of all US workers, and 49.41% of non-SSS workers. In other words, non-SSS workers in high-density commuting zones have borne a disproportionate share of the pandemic's economic fallout.

## LOOKING AHEAD

The recent pandemic provides some insights into what a transition towards more remote work may look like.

First, if the COVID-19 experience serves as a guide, the transition will be most disruptive in the densest U.S. cities. These cities employ the largest shares of workers able to work remotely, but at the same time are the most expensive places to live. As workplace proximity considerations become less important to residential decisions, these cities stand to lose part of their workforce.

Second, the worker-level impact of the transition will be very heterogeneous. High-skill service workers gain flexibility in their residential choices. Such changes in residential choices of high-income earners, endanger the economic livelihood of low-skill service workers in big cities who depend on local consumer services demand.[19] As a

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

result, big cities may not only lose their high-skill service workers, but also the local consumer service economies these workers support.

A more hopeful implication is that the transition to remote work could alleviate the pressure on big cities' housing markets (see Couture, Gaubert, Handbury, and Hurst, 2019). During the pandemic, SSS workers demonstrated a high willingness and ability to relocate and big cities' rents have declined substantially. Encouraging some of these workers to move more permanently could help reduce rents in city centers.

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. Gathergood and Guttman-Kenney (2020) is another paper focusing on changes in consumer spending in response to COVID-related lockdowns in the UK. Lee, Park, and Shin (2021) show that beyond the differential impact of the pandemic driven by industry of employment, gender, race and ethnicity, age, and education level are important determinants of its impact on individuals.

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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 those that 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) popularized in the economics literature by Autor and Dorn (2013). We use the crosswalks provided by Autor and Dorn (2013) to map Public-use Microdata Area (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 excluded 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.[20]

**Facebook Work From Home Data** We use county-level data on the fraction of residents who stay in a small area surrounding their home throughout a given day from

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

Facebook's Movement Range Maps. 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 only include weekdays in our analysis.

We assume that the fraction of people staying at home is a proxy for a fraction of people working from home. Figure A.1 confirms that this proxy reflects the main patterns in the fraction of people working from home measured by survey data, while broadly underestimating the fraction in levels.

Only users of Facebook's mobile application who opt into location history and background location collection are included. People whose location is not observed for a meaningful period of the day are excluded before computing county-wide measures.[21] For some counties the Facebook data is missing, we simply drop these counties from our sample. All our graphs compute averages within density or SSS employment bins over non-missing observations. As long as dropped counties are not very different from other counties with similar population density or SSS employment, dropping counties with missing data should not meaningfully affect our results.

**The New York Times COVID Data** We use data on the number of COVID cases recorded by county from the New York Times. We first transform cumulative case counts into absolute case counts. We then aggregate them from daily to monthly levels. Lastly, we divide the number of new COVID cases by the county's population.[22]

**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. Counties for which the data by Couture et al. (2020) is missing are excluded from our sample. All our graphs compute averages within density or SSS employment bins over non-missing observations. Our results are only affected by these missing observations if the available data is not representative for commuting zones.

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

[21] 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/

[22] For more information on the New York Times data, see https://github.com/nytimes/covid-19-data

**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.

We define consumer service establishments to include the following categories as defined by SafeGraph: Amusement Parks and Arcades; Beer, Wine, and Liquor Stores; Book Stores and News Dealers; Clothing Stores; Department Stores; Drinking Places (Alcoholic Beverages); Drycleaning and Laundry Services; Electronics and Appliances Stores; Florists; Furniture Stores; Gambling Industries; General Merchandise Stores, including Warehouse Clubs and Supercenters; Grocery Stores; Health and Personal Care Stores; Home Furnishings Stores; Jewelry, Luggage, and Leather Goods Stores; Lawn and Garden Equipment and Supplies Stores; Other Miscellaneous Store Retailers; Other Motor Vehicle Dealers; Personal Services; Performing Arts Companies; Personal Care Services; RV (Recreational Vehicle) Parks and Recreational Camps; Restaurants and Other Eating Places; Shoe Stores; Specialty Food Stores; Spectator Sports; Sporting Goods, Hobby, and Musical Instrument Stores; Traveler Accommodation; and Used Merchandise Stores.

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.[23]

**Zillow Data** We use monthly data on ZIP-Code-level average rental rates for apartments. The Zillow Observed Rent Index (ZORI) is a smoothed measure of the typically observed market rental rate across ZIP Codes. Only listed rents that fall into the 40th to 60th percentile range for all homes and apartments in a given region are included.[24]

[23] "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

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

We compute the average change in the ZORI index relative to January 2020 for all ZIP Codes within a county. We then subtract the monthly national median change in the ZORI, i.e., the unweighted median increase over all counties, from each county's change.

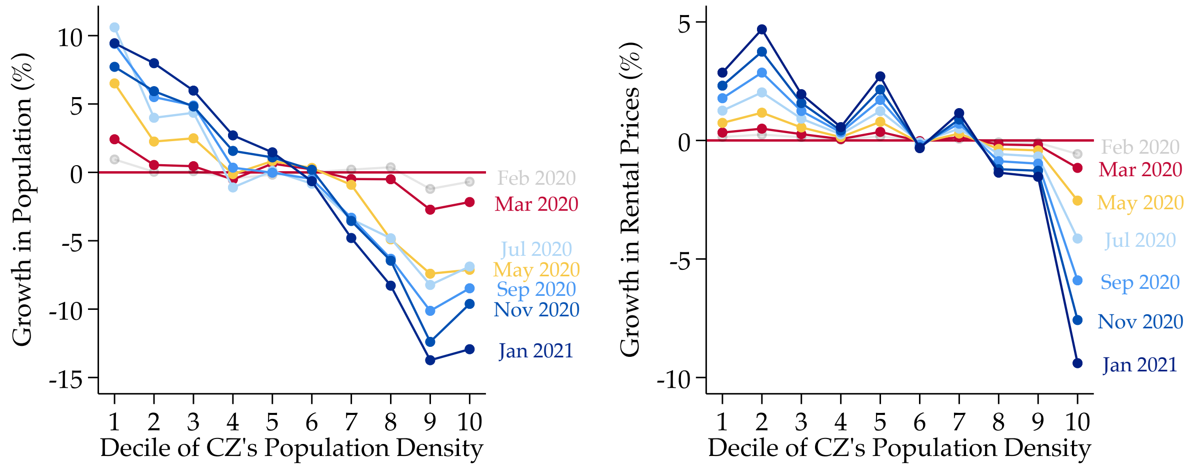
# B. Additional Exhibits

Table A.1: Average Earnings and Remote Work Potential by Industry in 2018

| Industry | Annual Income (USD) | Remote Work Potential (%) |
|---|---|---|
| SSS | 84,000 | 79.6 |
| Non-SSS | | |
| Resources + Construction | 54,900 | 19.7 |
| Manufacturing | 60,900 | 32.1 |
| Trade + Transport | 40,300 | 22.5 |
| Education + Medical | 48,500 | 50.6 |
| Arts + Hospitality | 22,600 | 14.4 |
| Other Services | 39,400 | 33.9 |

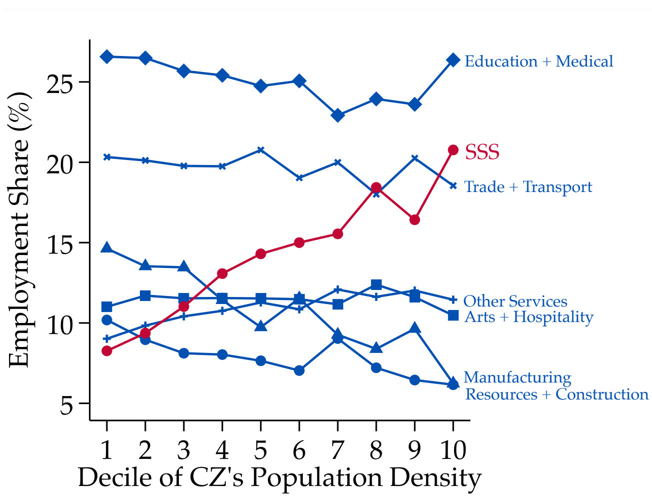
*Notes*: We use 2018 employment and income data from the pooled American Community Survey from 2014-2018. SSS includes NAICS industries 51, 52, 54, or 55 (see Eckert, Ganapati, and Walsh, 2020). Resources + Construction includes NAICS industries 21, 22, and 23; Manufacturing includes 31, 32, and 33; Trade + Transport includes 42, 44, 45, 48, and 49; Education + Medical includes 61 and 62; Arts + Hospitality includes 71 and 72; and Other Services includes 53, 56, and 81. We exclude the remaining NAICS industries, 11 (agriculture, forestry, fishing and hunting) and 92 (public administration), from our analysis. Annual income is computed as the average over an industry's workers with non-zero wage income measured in 2018-USD. Figures are rounded to hundreds. For remote work potential, we use the occupation-specific "work-at-home" classification by Dingel and Neiman (2020). We drop data for Alaska, Hawaii, and Washington, D.C., from our sample.

FIGURE A.1: POPULATION GROWTH AND RENTAL HOME PRICES




*Notes*: For the left panel, we use data from PlaceIQ to construct a measure of local population growth relative to January 2020 on the commuting zone level. For the right panel, we use ZIP-level data provided by Zillow on the price growth among rental homes. The series display changes in the population-weighted average of rental prices relative to January 2020 in each commuting zone net of the national median of price changes. We order commuting zones by their population density and then split them into ten groups of increasing density, each accounting for about one tenth of the U.S. population. To derive commuting zone population density, we follow Glaeser and Kahn (2004) in computing the population-weighted average of the population density across commuting zones' ZIP Codes. We use ZIP Code total population from the 2015-2019 American Community Survey. We drop data for Alaska, Hawaii, and Washington, D.C., from our sample.

FIGURE A.2: INDUSTRY EMPLOYMENT ACROSS CITIES




*Notes*: We use industry employment data from the pooled American Community Survey from 2014-2018. 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, 2020). We order commuting zones by their population density and then split them into ten groups of increasing density, each accounting for about one tenth of the U.S. population. To derive commuting zone population density, we follow Glaeser and Kahn (2004) in computing the population-weighted average of the population density across commuting zones' ZIP Codes. We use ZIP Code total population from the 2015-2019 American Community Survey. We drop data for Alaska, Hawaii, and Washington, D.C., from our sample.

TABLE A.2: THE IMPACT OF THE REMOTE WORK SHOCK ON CITY NEIGHBORHOODS EXCLUDING NEW YORK CITY AND SAN FRANCISCO

| | Growth in | | | | | |
|---|---|---|---|---|---|---|
| | Population (SafeGraph) | Population (PlaceIQ) | Rental Prices (Zillow) | Stay at Home (Facebook) | Foot Traffic (SafeGraph) | Consumer Spending (Affinity) |
| SSS Employment Share × | | | | | | |
| February 2020 | -6.183*** | -5.477 | -3.455*** | | -10.769 | 2.305 |
| | (1.722) | (3.950) | (0.281) | | (7.036) | (8.013) |
| March 2020 | -2.524 | -22.040*** | -6.934*** | 449.558*** | -84.273*** | -24.888** |
| | (3.963) | (7.834) | (0.589) | (47.487) | (5.931) | (10.156) |
| April 2020 | -60.599*** | -64.803*** | -10.373*** | 572.943*** | -137.524*** | -96.051*** |
| | (5.167) | (16.695) | (0.874) | (58.220) | (7.415) | (12.275) |
| May 2020 | -43.168*** | -64.725*** | -14.673*** | 444.258*** | -128.269*** | -107.086*** |
| | (5.460) | (14.228) | (1.254) | (44.090) | (9.764) | (16.339) |
| June 2020 | -41.272*** | -49.126*** | -18.875*** | 305.349*** | -91.401*** | -86.522*** |
| | (5.012) | (13.385) | (1.636) | (34.627) | (9.372) | (20.077) |
| July 2020 | -34.249*** | -71.237*** | -22.922*** | 250.752*** | -92.995*** | -79.013*** |
| | (6.725) | (19.321) | (1.963) | (30.737) | (11.841) | (22.529) |
| August 2020 | -22.937*** | -71.620*** | -27.124*** | 228.125*** | -82.249*** | -83.270*** |
| | (6.300) | (17.396) | (2.375) | (30.012) | (10.852) | (19.479) |
| September 2020 | -14.350** | -63.182*** | -31.460*** | 226.117*** | -78.641*** | -66.478*** |
| | (6.551) | (12.938) | (2.742) | (30.749) | (9.704) | (18.713) |
| October 2020 | -11.902* | -43.751*** | -35.214*** | 208.142*** | -76.643*** | -59.056*** |
| | (6.284) | (13.966) | (3.230) | (29.065) | (8.810) | (18.548) |
| November 2020 | 0.650 | -60.813*** | -39.490*** | 210.155*** | -74.431*** | -57.646*** |
| | (4.810) | (17.178) | (3.594) | (27.536) | (14.519) | (17.057) |
| December 2020 | -0.703 | -78.261*** | -44.421*** | 232.973*** | -54.543*** | -51.270** |
| | (5.098) | (21.911) | (4.024) | (29.901) | (8.654) | (20.520) |
| January 2021 | 6.576 | -80.240*** | -49.521*** | 248.073*** | -77.540*** | -79.172*** |
| | (4.531) | (19.669) | (4.287) | (33.120) | (8.008) | (24.603) |
| CZ×Month-FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted R-squared | 0.229 | 0.476 | 0.512 | 0.942 | 0.125 | 0.697 |
| Level of Observation | ZIP | County | ZIP | County | ZIP | County |
| Observations | 466,037 | 25,701 | 29,717 | 28,939 | 407,943 | 20,189 |

*Notes*: This Table replicates Table 2, but excludes the top-decile of commuting zones in terms of population density. We combine the data sets of SafeGraph, PlaceIQ, Zillow, Facebook, and Affinity to measure local outcomes at the ZIP- or county-level (see Appendix A). The dependent variable of all regressions is each outcome's monthly percent growth over its January 2020 baseline (February 2020 if the data is unavailable prior to that). We present estimates on the interaction of the local SSS employment shares and time dummies. All regressions are population-weighted and control for commuting zone × time fixed effects. 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, 2020). We use ZIP Code total population from the 2015-2019 American Community Survey. We drop data for Alaska, Hawaii, and Washington, D.C., from our sample. Standard errors are clustered at the commuting zone-level and stated in parentheses. *** significant at the 1 percent level, ** significant at the 5 percent level, * significant at the 10 percent level.

TABLE A.3: THE IMPACT OF THE REMOTE WORK SHOCK ON CITY NEIGHBORHOODS MEASURING SSS EMPLOYMENT SHARES BY PLACE OF WORK

| | Growth in Foot Traffic (SafeGraph) |
|---|---|
| SSS Employment Share × | |
| February 2020 | -4.556* |
| | (2.436) |
| March 2020 | -26.985*** |
| | (2.083) |
| April 2020 | -41.116*** |
| | (1.975) |
| May 2020 | -45.844*** |
| | (2.443) |
| June 2020 | -46.850*** |
| | (2.544) |
| July 2020 | -46.774*** |
| | (3.234) |
| August 2020 | -40.348*** |
| | (2.863) |
| September 2020 | -33.754*** |
| | (2.637) |
| October 2020 | -31.133*** |
| | (2.910) |
| November 2020 | -29.987*** |
| | (3.132) |
| December 2020 | -25.994*** |
| | (2.558) |
| January 2021 | -24.240*** |
| | (2.594) |
| CZ×Month-FE | Yes |
| Adjusted R-squared | 0.211 |
| Level of Observation | ZIP |
| Observations | 345,200 |

*Notes*: This Table replicates Table 2, but measures the SSS employment share by place of work, rather than place of residence. We combine the data sets of SafeGraph, PlaceIQ, Zillow, Facebook, and Affinity to measure local outcomes at the ZIP- or county-level (see Appendix A). The dependent variable of all regressions is each outcome's monthly percent growth over its January 2020 baseline (February 2020 if the data is unavailable prior to that). We present estimates on the interaction of the local SSS employment shares and time dummies. All regressions are population-weighted and control for commuting zone × time fixed effects. 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, 2020). We use ZIP Code total population from the 2015-2019 American Community Survey. We drop data for Alaska, Hawaii, and Washington, D.C., from our sample. Standard errors are clustered at the commuting zone-level and stated in parentheses. *** significant at the 1 percent level, ** significant at the 5 percent level, * significant at the 10 percent level.

## TABLE A.4: THE IMPACT OF THE REMOTE WORK SHOCK ON CITY NEIGHBORHOODS INCLUDING CONTROL FOR LOCAL COVID CASES

| | Growth in | | | | | |
|---|---|---|---|---|---|---|
| | Population (SafeGraph) | Population (PlaceIQ) | Rental Prices (Zillow) | Stay at Home (Facebook) | Foot Traffic (SafeGraph) | Consumer Spending (Affinity) |
| SSS Employment Share × | | | | | | |
| February 2020 | -30.611** | 0.701 | -3.495*** | | -47.037*** | -0.242 |
| | (13.149) | (11.054) | (0.318) | | (12.312) | (9.548) |
| March 2020 | -3.681 | -43.258** | -7.006*** | 386.471*** | -80.950*** | -43.244*** |
| | (4.059) | (20.117) | (0.459) | (63.599) | (5.530) | (7.994) |
| April 2020 | -65.866*** | -105.760*** | -10.223*** | 481.903*** | -130.052*** | -113.643*** |
| | (7.489) | (35.898) | (0.795) | (89.180) | (6.923) | (11.965) |
| May 2020 | -49.591*** | -105.362*** | -15.065*** | 390.801*** | -127.545*** | -127.682*** |
| | (8.496) | (37.292) | (1.008) | (58.693) | (8.251) | (15.026) |
| June 2020 | -47.849*** | -88.703** | -19.559*** | 282.680*** | -99.238*** | -113.821*** |
| | (9.080) | (36.947) | (1.334) | (36.194) | (9.143) | (19.024) |
| July 2020 | -40.079*** | -101.832*** | -23.710*** | 234.315*** | -98.261*** | -103.395*** |
| | (10.167) | (32.879) | (1.594) | (28.512) | (10.957) | (19.189) |
| August 2020 | -27.561*** | -98.430*** | -28.237*** | 216.602*** | -85.454*** | -98.716*** |
| | (8.425) | (27.015) | (1.884) | (27.440) | (9.557) | (14.784) |
| September 2020 | -17.445** | -84.601*** | -32.926*** | 210.036*** | -82.985*** | -96.377*** |
| | (7.319) | (20.429) | (2.253) | (28.572) | (10.365) | (22.847) |
| October 2020 | -11.467* | -64.755*** | -37.043*** | 193.300*** | -74.024*** | -93.809*** |
| | (5.994) | (19.198) | (2.608) | (26.964) | (8.105) | (24.627) |
| November 2020 | 2.133 | -85.030*** | -41.248*** | 194.782*** | -71.514*** | -86.039*** |
| | (4.588) | (21.295) | (2.822) | (25.854) | (12.788) | (21.570) |
| December 2020 | -2.245 | -97.149*** | -45.326*** | 218.149*** | -68.719*** | -72.177*** |
| | (4.751) | (21.401) | (2.797) | (32.374) | (8.453) | (16.730) |
| January 2021 | 3.425 | -98.868*** | -51.051*** | 234.399*** | -81.004*** | -115.516*** |
| | (4.996) | (19.608) | (3.122) | (31.201) | (7.167) | (31.199) |
| CZ×Month-FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Per-capita COVID cases | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted R-squared | 0.239 | 0.474 | 0.611 | 0.923 | 0.107 | 0.682 |
| Level of Observation | ZIP | County | ZIP | County | ZIP | County |
| Observations | 397,525 | 21,812 | 28,484 | 26,054 | 351,139 | 17,054 |

*Notes*: This Table replicates Table 2, but includes monthly COVID cases per capita on the county-level as an additional control. The COVID data comes from Johns Hopkins Corona Virus Resource Center (`https://coronavirus.jhu.edu/`). We combine the data sets of SafeGraph, PlaceIQ, Zillow, Facebook, and Affinity to measure local outcomes at the ZIP- or county-level (see Appendix A). The dependent variable of all regressions is each outcome's monthly percent growth over its January 2020 baseline (February 2020 if the data is unavailable prior to that). We present estimates on the interaction of the local SSS employment shares and time dummies. All regressions are population-weighted and control for commuting zone × time fixed effects. 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, 2020). We use ZIP Code total population from the 2015-2019 American Community Survey. We drop data for Alaska, Hawaii, and Washington, D.C., from our sample. Standard errors are clustered at the commuting zone-level and stated in parentheses. *** significant at the 1 percent level, ** significant at the 5 percent level, * significant at the 10 percent level.

## Table A.5: The Impact of the Remote Work Shock on City Neighborhoods Including Control for Neighborhood Population Density

| | Growth in | | | | | |
|---|---|---|---|---|---|---|
| | Population (SafeGraph) | Population (PlaceIQ) | Rental Prices (Zillow) | Stay at Home (Facebook) | Foot Traffic (SafeGraph) | Consumer Spending (Affinity) |
| SSS Employment Share × | | | | | | |
| February 2020 | -8.946** | -4.139 | -3.596*** | | -21.681** | 5.795 |
| | (3.789) | (3.772) | (0.247) | | (8.482) | (7.397) |
| March 2020 | -3.914 | -43.710** | -7.101*** | 390.777*** | -82.358*** | -30.327*** |
| | (3.926) | (19.721) | (0.482) | (62.415) | (5.448) | (8.100) |
| April 2020 | -65.666*** | -105.953*** | -10.708*** | 479.786*** | -130.011*** | -100.673*** |
| | (7.614) | (38.174) | (0.719) | (90.674) | (7.114) | (11.475) |
| May 2020 | -49.461*** | -105.413*** | -15.187*** | 390.072*** | -127.518*** | -115.027*** |
| | (8.536) | (37.944) | (1.033) | (58.715) | (8.288) | (14.630) |
| June 2020 | -47.795*** | -88.685** | -19.608*** | 283.015*** | -99.390*** | -101.224*** |
| | (9.015) | (36.591) | (1.354) | (36.200) | (9.130) | (18.568) |
| July 2020 | -40.071*** | -101.798*** | -23.873*** | 234.892*** | -98.380*** | -90.798*** |
| | (10.093) | (32.315) | (1.628) | (28.514) | (10.939) | (18.903) |
| August 2020 | -27.554*** | -98.533*** | -28.471*** | 214.596*** | -84.526*** | -85.909*** |
| | (8.600) | (28.419) | (2.004) | (26.720) | (9.674) | (14.592) |
| September 2020 | -17.438** | -84.663*** | -33.022*** | 208.800*** | -82.440*** | -83.666*** |
| | (7.418) | (21.232) | (2.322) | (28.183) | (10.426) | (22.244) |
| October 2020 | -11.479* | -64.899*** | -37.177*** | 190.569*** | -72.913*** | -80.973*** |
| | (6.127) | (20.941) | (2.719) | (26.097) | (8.070) | (24.350) |
| November 2020 | 2.111 | -85.245*** | -41.652*** | 190.865*** | -69.763*** | -73.068*** |
| | (4.658) | (23.660) | (3.045) | (24.428) | (12.551) | (21.310) |
| December 2020 | -2.295 | -97.806*** | -46.419*** | 206.445*** | -64.781*** | -58.523*** |
| | (5.383) | (23.110) | (3.287) | (28.207) | (9.095) | (17.092) |
| January 2021 | 3.388 | -99.371*** | -51.821*** | 225.539*** | -78.690*** | -102.045*** |
| | (5.742) | (21.393) | (3.584) | (28.783) | (7.190) | (31.392) |
| CZ×Month-FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Population Density | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted R-squared | 0.271 | 0.579 | 0.652 | 0.941 | 0.140 | 0.703 |
| Level of Observation | ZIP | County | ZIP | County | ZIP | County |
| Observations | 479,427 | 26,078 | 32,428 | 29,287 | 421,253 | 20,540 |

*Notes*: This Table replicates Table 2, but includes county/ZIP code-level population density as an additional control. We combine the data sets of SafeGraph, PlaceIQ, Zillow, Facebook, and Affinity to measure local outcomes at the ZIP- or county-level (see Appendix A). The dependent variable of all regressions is each outcome's monthly percent growth over its January 2020 baseline (February 2020 if the data is unavailable prior to that). We present estimates on the interaction of the local SSS employment shares and time dummies. All regressions are population-weighted and control for commuting zone × time fixed effects. 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, 2020). We use ZIP Code total population from the 2015-2019 American Community Survey. We drop data for Alaska, Hawaii, and Washington, D.C., from our sample. Standard errors are clustered at the commuting zone-level and stated in parentheses. *** significant at the 1 percent level, ** significant at the 5 percent level, * significant at the 10 percent level.