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The Geography of Remote Work[☆]

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ABSTRACT

High-income business service workers dominate the economies of major US cities, and their spending supports many local consumer service jobs. As a result, business services' high remote work potential poses a risk to consumer service workers who could lose an essential source of revenue if business service workers left big cities to work from elsewhere. We use the COVID-19-induced increase in remote work to provide empirical evidence for this mechanism and its role in shaping the pandemic's economic impact. Our findings have broader implications for the distributional consequences of the transition to more remote work.

1. Introduction

The economies of big cities in the United States largely consist of highly educated workers specialising in business services and less educated workers in non-tradable consumer service industries (see Eckert et al., 2020). The consumer service industries depend on the demand of business service workers for service offerings like restaurants, haircuts, and childcare (see Glaeser et al., 2001). The relationship between these two groups of service workers is unbalanced: the livelihood of consumer service workers depends directly on the local spending of high-skill business service workers, while the converse is not true.

With improvements in technology and high-speed internet, many business service jobs can now be done remotely, so that big cities' specialization in business services has translated into a specialization in remote work jobs. Until recently, this elevated potential for remote work was inconsequential, since the vast majority of workers did not make use of it (see Bloom et al., 2015). However, the recent COVID-19 pandemic has accelerated the transition to actual remote work practices.

Such a transition is likely to affect business and consumer service workers differently due to the differences in markets served. As high-skill service workers transition to remote work, they become more mobile, and may leave big city centers with high rents for regions with lower costs of living or more favorable amenities. When they depart big cities, they take their demand for consumer services with them. As a result, the transition to remote work is likely to hurt less-mobile consumer service workers in big cities the most.

In this paper, we use the sudden rise in remote work during the COVID-19 pandemic to provide empirical evidence for this mechanism. We proceed in in three steps.

First, we show that a large fraction of business service jobs can be done remotely and are concentrated in big, expensive cities. Together, these patterns generate a positive relationship between population density and remote work potential. The rise of remote work during the pandemic translated big cities' elevated remote work potential into

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actual remote work: throughout the pandemic, cities with high population density saw more than twice the share of its workforce work remotely than less dense cities. Business service industries account for these differences: more than 50% of their workforce worked remotely during the first months of the pandemic, almost twice the percentage of any other industry. These findings imply that consumer service workers in big cities are particularly exposed to changes in the geography of consumer spending that remote work practices may entail.

Second, we provide evidence that business service workers left their big city residences during the COVID-19 pandemic to work from elsewhere as remote work became more prevalent. Cell phone data shows that ZIP codes with a high share of business service workers among their residents at the beginning of the pandemic saw particularly large outflows of workers, and that these workers relocated to places with lower population density. Corroborating these findings, we show that, in ZIP codes with high pre-pandemic shares of business service workers, both declines in residential rents and increases in work-from-home practices were more pronounced than in other locations.

Third, we study the impact of the change in business service workers' location decisions on the consumer service industries they leave behind. Consumer service spending declined most in locations within cities with large pre-pandemic shares of business service workers among their residents. The same locations also saw large declines in visits to consumer service establishments of any kind. Worker-level data shows that consumer service workers in big cities saw their hours decline more than consumer service workers in smaller cities in which business service industries are less important. Simultaneously, hours of business service workers show similar dynamics in both big and small cities, reflecting that these workers do not depend on local demand. Overall, we show that non-tradable service workers in big cities lost more hours of work during the pandemic than their peers in smaller cities, or business service workers anywhere; they bore the brunt of the pandemic's economic impact.

Our findings highlight the one-way dependence of non-tradable service workers on the local spending of workers in high-paying business service industries, and have implications for the transition to remote work more generally. Our analysis shows that the transition to more remote work is likely to affect regions and workers differently depending on their remote work potential. Using the COVID-19 pandemic as a guide, high-education service workers are likely to use the increased spatial flexibility afforded to them by remote work practices. Less-educated consumer service workers may suffer from their dependence on local demand, especially as they find it harder to respond to local wage changes through migration (Notowidigdo, 2020).

Big cities themselves face a dual threat: they may not only lose their increasingly mobile high-skill workers, but also the local consumer service economies these workers support. As a result, such cities 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.

Related Literature. Our work contributes to an emerging literature on the nature and implications of increased remote work in the US economy.

A number of recent papers have constructed occupation-based measures for remote work *potential* (see Dingel and Neiman, 2020 and Mongey et al., 2021). Another set of papers validate these measures by comparing them to actual work from home percentages during the pandemic (Barrero et al., 2021; Brynjolfsson et al., 2020; DeFilippis et al., 2020; Bick et al., 2020). Our paper uses these occupation-based measures to show the strong relationship between city population density and remote work potential in the cross-section of all US cities, and validate it with actual remote work measures during the pandemic. We also establish differences in industrial structure as the central determinant of this relationship: a city's business service employment share predicts its remote work potential almost perfectly.

A related strand of literature discusses the implications of the COVID-19 pandemic on the US economy. A first set of papers focuses on the heterogeneous impact on different types of workers, e.g., Mongey et al. (2021), Chetty et al. (2020), Alon et al. (2020), and Glaeser et al. (2020). A second group of papers focuses on the impact of remote work on city-level outcomes, e.g., the location of residence (Ramani and Bloom, 2021), residential rents and house prices (Liu and Su, 2021), and migration flows (Coven et al., 2020).[1] Our paper adds to this literature by highlighting two important determinants of exposure to remote work not previously discussed. First, we provide direct evidence for the difference in exposure of business and non-tradable service workers, and offer a concrete economic mechanism explaining this difference. Second, our work suggests that cities stand to be affected differently by the transition to remote work as a result of their industrial specialization.[2]

Our paper also relates to prior work documenting that while big cities offer high returns to skilled workers, they provide fewer and fewer opportunities to other types of workers, including Autor (2019), Eeckhout et al. (2014), and Davis, Mengus, and Michalski (2021a). Our work presents a concrete mechanism through which the transition to remote work hurts less educated consumer service workers and benefits highly educated business service workers, further exacerbating existing inequalities between these groups.

2. The mechanism

In this section, we outline an extension of the classic Rosen-Roback model to formalize our mechanism. Appendix C provides the equations underlying the results presented here.

Setup. Consider an economy that consists of a set of locations. In each location, there is a tradable and a non-tradable sector. We refer to the workers in the tradable sector as business service workers. Workers cannot change sector but can freely choose their location. Locations differ in amenities and productivity for business service workers. The productivity and amenities for non-tradable service workers are identical across locations. We assume that the more tradable service workers are in a location, the more congested are its amenities. This serves as a reduced form for the increased cost of living in more populated locations.

Spatial Equilibrium. In equilibrium, the size of a city's business service sector depends only on the underlying productivity of a location and the amenities offered to its workers. The size of the non-tradable service sector in a location is proportional to the size of the local business service sector: non-tradable service workers depend on the demand generated by the local business service sector. Business service workers choose locations without regard to the size of the local market for their services, while the location choices for non-tradable service workers are solely driven by market size.

A Remote Work Technology. We model the arrival of a remote work technology as a sudden equalization of locations' productivity for business service workers. This is a stylized way of capturing that workers' locations are less relevant to the productivity of their work if remote work is feasible.

We are interested in the immediate impact of the arrival of a remote work technology rather than a new steady state featuring it. Con-

[1] Other papers have emerged documenting the reallocation of workers away from dense and expensive locations, e.g., Couture et al. (2021), Haslag and Weagley (2021), and Florida and Ozimek (2021). De Fraja et al. (2021) extend our analysis to the UK where they look at the incidence of work-from-home across neighborhoods.

[2] Theoretically, several papers trace out the general equilibrium implications of more remote work for the allocation of workers within (see Delventhal et al. (2021) and across cities Delventhal and Parkhomenko (2020)). Generally these papers imply that residents that can work remotely reallocate away from initially expensive areas within cities, underscoring the core premise of the mechanism we highlight.

Table 1
Average earnings and remote work potential by industry in 2018.

Industry	Annual Income (USD)	Remote Work Potential (%)
Skilled Scalable Services (SSS)	84,000	79.6
Other Industries		
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 to 2018. SSS includes NAICS industries 51, 52, 54, or 55 (see Eckert et al., 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.

sequently, we assume that business service workers can relocate in response to a remote work shock, while non-tradable workers cannot.[3]

Predictions. The model predicts that business service workers leave formerly productive cities and move to less congested ones in response to a remote work shock. As a result, immobile consumer service workers see their wages decline most in the formerly most productive and attractive cities as the business service workers withdraw their demand for local non-tradables.

A large literature documents that big cities are more attractive places to live (e.g., Diamond, 2016; Eckert et al., 2020) and are more productive (e.g., Roca and Puga, 2017). Given that, our theory makes the following testable predictions for the direct effect of a remote work shock:

1. Big cities should see larger outflows of business service workers as remote work becomes possible, compared to smaller cities.
2. Average wages of non-tradable service workers in big cities should fall more than those of non-tradable service workers in smaller cities.

The COVID-19 pandemic presented a remote work shock as it made such work possible and necessary for large parts of the US workforce. Combined with its sudden onset, the pandemic hence provides an opportunity to test the two predictions of our theory.[4]

Before testing our mechanism using data on the relocation of workers across ZIP codes and local consumer service spending, we first document two empirical regularities necessary for our mechanism to be operational. First, that business service workers were actually much more likely to work remotely during the pandemic than other types of workers. Second, business service workers are disproportionately concentrated in big expensive cities, so that they have an incentive to relocate once remote work allows them to.

3. The geography of remote work

In this section, we show that business service workers have the highest remote work potential among all industries in the US economy, and are concentrated in the largest US cities. Since dense cities are expensive places to live, these facts imply that increases in actual remote work may induce location changes of business service workers in line with our mechanism. We also show that the increase in remote work across cities during the recent pandemic reflected these patterns, making it a useful setting to test our mechanism.

3.1. Remote work potential across industries and cities

We start by documenting that business service industries exhibit substantially higher remote work potential than other industries, and that they are concentrated in large and expensive cities. We use the occupation-based work-from-home classification introduced by Dingel and Neiman (2020) and merge it onto micro-data from the American Community Survey.[5] We follow Eckert et al. (2020) and define business service industries as the following set of 2-digit NAICS codes: 51 (Information), 52 (Finance and Insurance), 54 (Professional Services), and 55 (Management of Companies), and as in that paper refer to them as "Skilled Scalable Services," or SSS in shorthand.

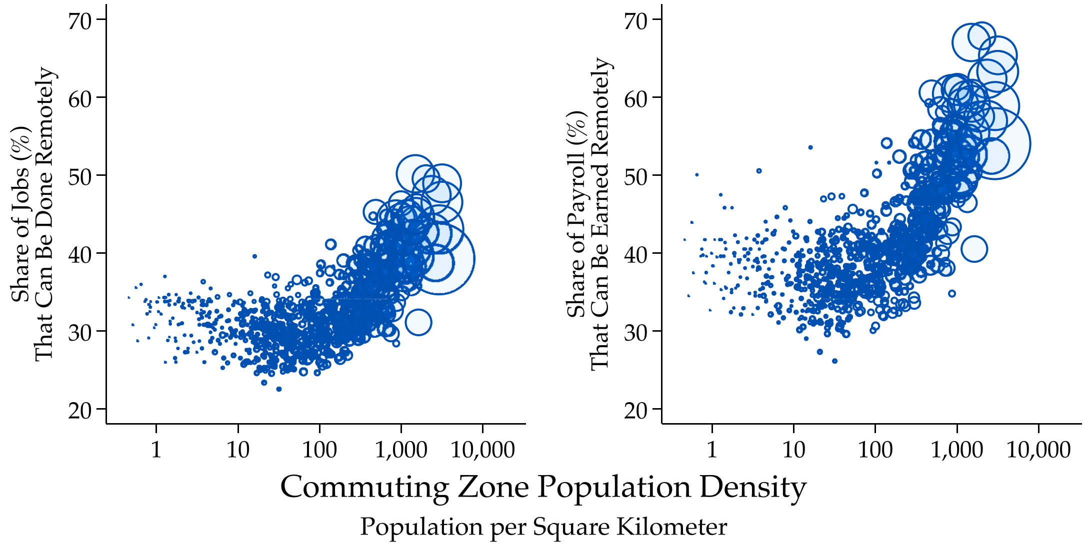
Table 1 shows the fraction of workers in each sector that could in theory work from home according to the Dingel and Neiman (2020) measure. SSS industries have the highest potential for remote work: almost 80% of workers in the these industries could work from home in theory. In addition, SSS workers also earn by far the highest average incomes, making them an important source of demand for local consumer services in their locations of residence. Figure A.1 in the Appendix shows that SSS industries are overwhelmingly located in cities with high population density, which are generally locations with a high cost of living.

Since most SSS jobs can be done remotely and are concentrated in big cities, big cities inherit these services' potential for remote work. The left panel of Fig. 1 plots the share of jobs that can be done remotely

[3] Notowidigdo (2020) provides direct evidence that low-skill workers move much less in response to wage changes than high-skill workers. Our results continue to hold as long as relocation costs are relatively higher for non-tradable compared to business service workers.

[4] The pandemic likely had another affect that interferes with these predictions. The pandemic forced workers to stay at home, further equalizing amenities across locations. Such an additional equalization of amenities generates interesting additional predictions which we discuss in Appendix C.

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



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). 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.

Fig. 1. Remote work potential across cities.

against commuting zone population density.[6] 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. In Section B.1 in the Appendix, we confirm that the share of business service workers among the local workforce accounts for the lion's share of the elevated remote work potential of denser cities.

In summary, business service industries have a very high remote work potential and dominate the economies of big, expensive cities in the US economy. These findings provide the initial conditions for our mechanism: as remote work becomes more possible, many business service workers are likely to leave big cities and withdraw demand from local consumer service industries.

3.2. Remote work during the COVID-19 pandemic

The COVID-19 pandemic drastically lowered the relative cost of remote work and led large parts of the US economy to start working remotely almost overnight (see Bartik et al., 2020; Bick et al., 2020).[7] In order to use the COVID-19 pandemic to study our mechanism of interest, we now show that the pandemic-induced remote work followed the patterns predicted by the theoretical measure in the previous section.

In May 2020, the US 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).[8] A convenient feature of the CPS is the breadth of other individual-level information contained in the data set, such as the initial location of residence and the industry of the respondent.[9]

We use the CPS data to document the rise of remote work across cities and industries during the pandemic. The left panel of Fig. 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 as that of the rest of the US 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.1 in the Appendix).

Next, we group commuting zones into ten bins of increasing density, each accounting for 10 percent of the US population.[10] The right panel of Fig. 2 shows the fraction of workers who worked remotely in various months of the pandemic for each of these ten commuting zone bins. The

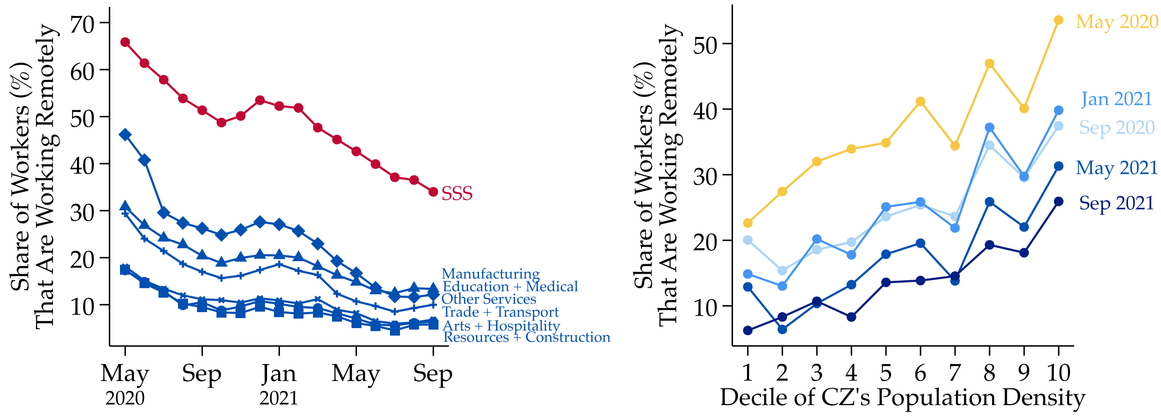
[6] Following Glaeser and Kahn (2004), we compute the population density of a commuting zone as a population-weighted average of the population density of its ZIP codes to take into account the spatial distribution of residents *within* them.

[7] Glaeser et al. (2020) show that commuting to work substantially increased workers' risk of contracting COVID-19. Prior to the pandemic 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 et al., 2012; Dingel and Neiman, 2020).

[8] Bick et al. (2020) report about 31% of workers working remotely in May, with an additional 13% working remotely part of the week. Brynjolfsson et al. (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%.

[9] 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.

[10] 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.



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 right 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 US 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.

Fig. 2. Remote work during the pandemic.

pandemic-induced rise in remote work was strikingly density-biased. In May 2020, more than 50 percent of workers in the densest cities worked remotely, compared to only 23 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 Fig. 1.

Figure A.3 in the Appendix replicates Fig. 2, but controls for COVID-19 cases in each industry and month (left panel) and commuting zone and month (right panel). Controlling for COVID cases leaves the patterns qualitatively and quantitatively unchanged: remote work is not higher for SSS workers or big-city workers because such workers are more exposed to COVID.[11]

While the overall level of remote work changes over the course of the pandemic, the industry and urban bias in remote work remains intact. Although the time series is short, the level of SSS workers continuing to work remotely remains very high two years on (up from essentially nothing before the pandemic), suggestive of a more permanent change.

In summary, the pandemic-induced remote work shock followed the prediction of the remote work potential measure from Dingel and Neiman (2020): business service industries showed the highest level of actual remote work, and big, expensive cities saw the largest fraction of local workers working remotely. These findings suggest that we can use the pandemic to provide evidence for our mechanism.

4. The mechanism in the data

In this section, we use the COVID-19-induced remote work shock to study the impact of a transition to more work-from-home on business and non-tradable service workers.

4.1. Research design

We document the impact of the pandemic-induced rise of remote work in two steps. First, we show that business service workers are much more likely to leave their original location of residence. Second, we show that consumer service workers dependent on these business service workers are hurt economically by the change in their location choices. Our approach is designed to overcome two challenges.

A first challenge is that none of our outcome data (migration flows and measures of consumer service spending) contain any individual characteristics. As a result, we use neighborhood-level variation in the share of local residents employed in the business service industries at the beginning of the pandemic for our analysis. We show that neighborhoods with a larger share of residents employed in business service industries saw greater outflows and a greater decline in demand for consumer services.

A second challenge is that urban density itself played a significant role in the propagation of the COVID-19 pandemic: larger cities were hit earliest and hardest (see Carozzi et al., 2020; Coven et al., 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. To overcome this challenge, 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.

We standardize all outcome variables by their standard deviation in that month. We can thus interpret the coefficient of "SSS employment share among local residents" in a given regression as "the increase in the number of standard deviations of the outcome variable for a 1 percentage point increase in the local SSS employment share among residents."

4.2. The mechanism in the data

We first provide evidence that ZIP codes that were home to more business service workers pre-pandemic saw larger outflows of work-

[11] Figure A.4 in the Appendix plots the share of potential remote work shares against the actual remote work shares for these ten commuting zone groups: in May 2020 the commuting zones lie along the 45° line suggesting that during the pandemic cities reached the full remote work potential predicted by the Dingel and Neiman (2020) measure.

Table 2
The impact of the remote work shock on city neighborhoods.

	Growth in				
	Population (SafeGraph)	Rental Prices (Zillow)	Stay at Home (Facebook)	Foot Traffic (SafeGraph)	Consumer Spending (Affinity)
SSS Employment Share × February 2020	−0.472***	−0.485***		0.006	0.087
	(0.058)	(0.039)		(0.009)	(0.395)
March 2020	−0.158**	−0.972***	15.418***	−0.151***	−1.838***
	(0.065)	(0.078)	(2.478)	(0.012)	(0.443)
May 2020	−0.640***	−2.050***	15.392***	−0.328***	−6.195***
	(0.095)	(0.181)	(2.332)	(0.023)	(0.807)
September 2020	−0.346***	−4.397***	8.241***	−0.223***	−3.870***
	(0.096)	(0.401)	(1.119)	(0.023)	(0.800)
January 2021	−0.198**	−5.641***	8.903***	−0.159***	−4.758***
	(0.083)	(0.551)	(1.142)	(0.021)	(1.002)
May 2021	−0.313***	−5.516***	4.440***	−0.319***	−2.960**
	(0.116)	(0.820)	(0.934)	(0.046)	(1.227)
September 2021	−1.234***	−5.195***	1.686**	−0.367***	−2.965**
	(0.134)	(1.128)	(0.794)	(0.061)	(1.264)
CZ × Month-FE	Yes	Yes	Yes	Yes	Yes
State-FE	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.082	0.823	0.944	0.018	0.758
Level of Observation	ZIP	ZIP	County	ZIP	County
Observations	774,501	41,791	46,082	659,102	35,421

Notes: We combine the data sets of SafeGraph, Zillow, Facebook, and Affinity to measure local outcomes at the ZIP- or county-level (see Appendix A). The dependent variable of all regressions is a standard deviation in each outcome's monthly percent growth over its January 2020 baseline (February 2020 if the data is unavailable prior to that). Appendix Table A.2 presents the same results in their non-standardized version. 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 and state 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 et al., 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.

ers to other locations. We then show the impact of these changes on the local consumer service industries in these ZIP codes. Finally, we present additional city-level evidence for an aggregate implication of our mechanism: the average consumer service worker in a large city lost more hours of work than their counterpart in a small city. In Appendix A, we provide more detail on all the data used in this section.

Impact on the Location of Work of SSS Workers. First, we show that within a given city, the larger the share of SSS workers among the residents of a ZIP code, 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 cumulative change 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 at the beginning of the pandemic saw larger subsequent population outflows.[12] 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 saw almost a 10 percent decline in their local population by the fall of 2020, whereas low-density commuting zones saw a more than 5 percent increase in the local population.[13] Together with the regression in Column 1 of Table 2, this suggests that SSS workers were making use of their ability to work remotely, disproportionately leaving their initial locations of residence.[14]

We provide two additional pieces of evidence that ZIP codes with more business service workers saw higher remote work rates than other ZIP codes.

First, Column 2 of Table 2 shows the impact of the outflow of SSS workers on the local rental market for housing. The higher the initial SSS share among the residents of a ZIP code, 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.2 in the Appendix).[15] These findings suggest that business service workers left their locations of residence at higher rates than other types of workers thereby increasing the housing supply in their former neighborhoods.

Second, we consider a direct 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 × 600 m 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.[16] The third column of Table 2 shows the increase in staying from home relative to March 2020 as a function of the initial

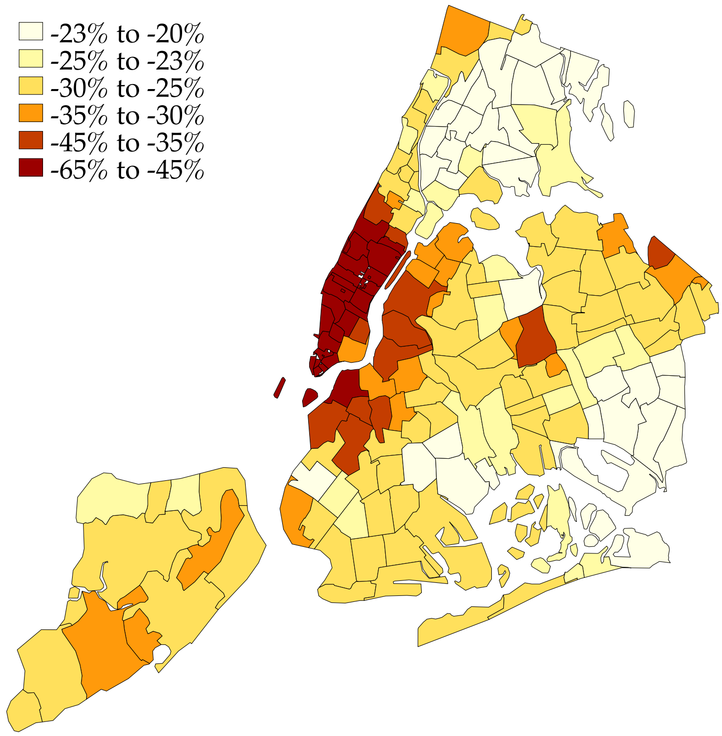
[12] Employment shares are expressed as fractions, i.e., they are bounded between zero and one.

[13] Davis, Ghent, and Gregory (2021b), Delventhal and Parkhomenko (2020), and Delventhal et al. (2021) provide theoretical models of telecommuting in response to the pandemic whose predictions are consistent with the empirical evidence we provide.

[14] Liu and Su (2021) provide a more comprehensive analysis of the effect of COVID-19-induced migration on housing prices throughout the United States. Cho, Lee, and Winters (2021) document early evidence that employment effects of the pandemic are much larger in larger MSAs.

[15] Rosenthal et al. (2021) provide similar results for commercial rents.

[16] 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 m by 600 m area around their home.



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.

Fig. 3. SSS residents and the decline in consumer spending in New York city.

SSS employment share among residents. It shows that staying at home increased strongly in counties with a larger initial SSS share among residents. The fact that work-from-home was more prevalent in counties with a lot of SSS workers provides additional evidence that remote work may also have been more prevalent in such locations, further supporting the findings from the population data in Column 1.

Overall, within cities, out-migration was biased towards ZIP codes and counties with disproportionate amounts of high-income, business service workers. For these SSS workers, an essential part of what makes dense cities attractive are the opportunities for local service consumption (see Glaeser et al., 2001). Next, we document the effect of SSS workers' departure on the local economies of their former neighborhoods of residence.

Impact on Consumer Service Industry. 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.[17] The change in such visits serves as a proxy measure for the changes in demand for consumer services in these ZIP codes in a given month.

Column 3 of Table 2 shows the decline in visits to consumer service establishments in each ZIP code as a function of the initial SSS employment share among its residents. The decline in foot traffic into local service establishments tracks the population change data closely. Within cities, ZIP codes with a larger initial share of SSS residents saw larger declines in visits to local consumer service establishments.[18] Of course, workers do not only consume local consumer services in their ZIP code of residence.[19] In Appendix Table A.4, we replicate the regression in Column 4 of Table 2 but interact the month with the SSS employment share among all *workers* in a given ZIP code. 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 et al. (2020) further allows us to measure consumer spending directly but only on the county, not the ZIP code level. The consumer spending data provides total spending on consumer services by a county's residents.[20] Column 5 of Table 2 shows the decline in consumer spending in each ZIP code as a function of the initial SSS employment share among its residents. These results corroborate the evidence from the cellphone data in Column 4: spending on consumer services declined significantly more in locations initially home to more SSS workers.

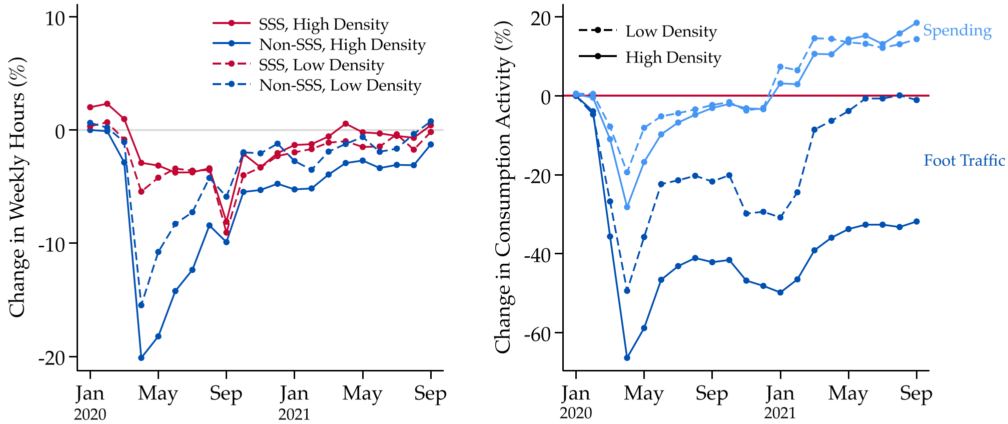
The estimates in Table 2 are economically meaningful. As an example, consider visits to consumer service establishments. In Fig. 3, we color each New York City ZIP code according to the decline in visits to

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

[18] This accords with the findings by Chetty 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.

[19] Work by Davis et al. (2019) and others suggests that location of residence is an important determinant of the location of consumption of consumer services such as restaurants.

[20] 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 county of residence and can hence not analyse change in spending around work locations since we do not know where individual workers work.



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.

Fig. 4. Employment outcomes during the pandemic.

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 its residents relative to some reference commuting zone. Affluent areas in Manhattan and Brooklyn, home to many SSS workers, saw visits to local consumer service establishments decline by twice as much as 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 do not claim to obtain precise causal estimates of the impact of remote work on local spending. It is not possible to control for all confounding unobservables without knowledge of what these may be. Nevertheless, our evidence strongly suggests that the mechanism outlined in Section I is active and economically important.

Robustness Exercises. Our analysis uses commuting-zone-month fixed effects to control for variation in the incidence of the pandemic across commuting zones and for commuting-zone-specific policies and restrictions. Of course, there is the possibility that some of our economic outcomes are also affected by restrictions or COVID incidence that vary across neighborhoods within the same city. If the incidence of COVID cases or restrictions is correlated with the fraction of SSS workers, this could bias our coefficient on the local SSS employment share. We conduct a set of robustness checks to ensure that such neighborhood level differences do not drive our results. We do not have systematic data on ZIP code level restrictions to directly control for highly-localized policies. Instead, we add controls for factors that are likely related to whether or not a policymaker would put in place such restrictions, in particular the local incidence of COVID cases.

Note that all our robustness checks replicate the regressions from Table 2 on different samples but without normalizing the outcome variables by their standard deviation. For comparability, Table A.2 replicates Table 2 without normalizing each outcome variable by its standard deviation.

Appendix Table A.5 shows that controlling directly for county-month level 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 for all ZIP codes of the United States. In Table A.8, we repeat our regressions but restricting ourselves to the cities for which we have ZIP code level data: New York, Chicago, San Francisco, and Santa Clara. The first three columns repeat the regressions for changes in population, rental prices, and foot traffic for this subset of cities. The second three columns then add in ZIP code level COVID cases per capita. Comparing the leftmost three columns to the rightmost three columns shows that controlling explicitly for local COVID incidence does not meaningfully change the estimated coefficients.

Additionally, we can proxy ZIP code level COVID incidence with ZIP code level population density since denser locations tended to have a higher incidence of COVID to start with. In Table A.6, 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 no meaningful effect on the regression coefficient estimates.

Finally, as an additional 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 the New York City and San Francisco commuting zones and find similar results.[21]

Cross-city Implications. Our mechanism suggests that since business service workers were concentrated in large expensive cities prior to

[21] The top density decile in Fig. 2 consists of New York and San Francisco only, since together they account for 10 percent of US employment. Our regression in the Appendix highlight that the relationship between work-from-home and density is similarly strong when they are excluded (see Figure A.3).

the pandemic, these cities should see the largest outflows of such workers and the largest decline in demand for consumer services during the pandemic.

We use the data from the Consumer Population Survey (CPS) to provide empirical evidence for this implication. The CPS provides a direct measure of employment outcomes for consumer service workers, weekly hours worked. Unfortunately, the CPS data is not available for counties or ZIP codes, so that we cannot include it in our analysis in Table 2.

The left panel of Fig. 4 shows the decline in hours in SSS and non-SSS jobs in high- and low-density commuting zones. We define high-density commuting zones as the most dense commuting zones that can jointly account for 50% of US 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. The pandemic presented a much more severe shock to the hours of non-SSS workers, including consumer service workers. Importantly, as predicted by our mechanism, non-SSS workers in big cities are hit much harder than their counterparts in small cities.

Together with the evidence in Table 2, the left panel of Fig. 4 suggests that consumer service workers in big cities saw a larger negative demand shock than their small city counterparts. The fact that the average SSS workers saw the same decline in hours in both types of cities suggests that they were subject to a similar economic shock regardless of their location of work. While Fig. 4 does not establish a causal relationship, it supports our narrative.

The right panel of Fig. 4 provides further evidence that the difference between non-SSS workers' economic outcomes in big and small cities is related to differences in the decline of consumer services 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. Both time series show a steep decline between March and April, with a slower recovery in big cities. The two time series follow those for non-SSS workers' losses in weekly hours remarkably well. Alongside the evidence in Table 2 this suggests that demand for consumer services declined more in big cities as the SSS workers that account for a large part of local consumption started to work from elsewhere.

The CPS data also reveals that by January 2021, non-SSS workers in high-density commuting zones accounted for almost 60% of all hours lost in the US economy in that month relative to the previous year. At the same time these workers accounted for only around 41.1% of all US workers, and 49.4% 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.

5. 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 US 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 central to residential decisions, these cities stand to lose part of their workforce.

Second, the worker-level impact of the transition will be heterogeneous. High-skill service workers gain flexibility in their residential choices. The resulting changes in residential choices of high-income earners may endanger the economic livelihood of less educated service workers in big cities who depend on local consumer services demand.[22] As a 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 et al., 2019). During the pandemic, SSS workers demonstrated a high willingness and ability to relocate, and big cities' rents declined substantially in response. Encouraging some of these workers to move more permanently could help reduce rents in city centers.

The future geography of work and residence will depend on whether the advantages of modern cities are primarily productive or in the quality of life they provide. In the former case, we could expect the prominence of large cities to diminish as remote work becomes feasible, whereas in the latter case, large and consumption-rich cities like New York are likely to continue to thrive. Using the continued aftermath of the COVID-induced remote work shock to distinguish between the drivers of urban concentration provides an interesting avenue for future research.

Declaration of competing interest

None of the authors have any conflicts of interest to disclose.

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 et al. (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.

[22] Almagro and Orane-Hutchinson (2020) and Almagro et al. (2021) 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 (2021) 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.

Current Population Survey We draw on the Current Population Survey (CPS), a monthly, nationally representative labor market survey conducted by the US 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 US. 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.[23]

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 Facebook's Movement Range Maps. Every smartphone user who does not leave their approximately 600 m by 600 m 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.2 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.[24] 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.[25]

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 US. 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 through specific apps. The data used in this paper is anonymized.

Ramani and Bloom (2021) find that workers moved from more dense to less dense 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 register with the Postal Service.

SafeGraph Population Data We use data on the number of smartphone users residing in each ZIP code by SafeGraph. The data is derived from 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 data set. The normalized monthly growth in devices by county is used as a proxy for population growth. All our graphs compute averages within density or SSS employment bins over non-missing observations.

We have successfully reproduced the migration patterns using other data sources, such as PlaceIQ (provided by Couture et al., 2021), VenPath (e.g., used in Coven et al., 2020), and DescartesLabs.

Couture et al. (2021) discuss the unique value that smartphone data creates by allowing researchers to study movement and social contact of people in real-time. They show that typically, these data cover a significant fraction of the US population and that the samples represent the US population well. They show that estimating county population using smartphone data captures 95 percent of the true variation in population across counties as reported in the Census. The authors also provide evidence that these data remained reliable throughout the COVID-19 pandemic.

While we do not have access to USPS data on address changes ourselves, we use secondary sources to compare the migration patterns suggested by that data to our estimates. The USPS data records address changes reported to USPS directly. Appendix Figure A.6 replicates a study on local population changes based on the USPS data by MyMove.[26] The two data sets suggest similar magnitudes in population changes across states. There are some discrepancies that may arise from the fact that our data captures moves of any kind while the USPS data only captures permanent moves reported as address changes. The comparison study also computes a ranking of the cities with the highest gains or losses in population. While we cannot compute relative changes for their data, we can compare their ranking to ours. Their top-5 cities in terms of population losses are New York

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

[24] 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/.

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

[26] https://www.mymove.com/moving/covid-19/coronavirus-moving-trends/.

(NY), Brooklyn (NY), Chicago (IL), San Francisco (CA), and Los Angeles (CA). The ranking suggested by our data (consisting of 17,057 cities as defined by USPS) is Los Angeles (CA), Chicago (IL), New York (NY), Brooklyn (NY), and Houston (TX). San Francisco (CA) ranks 7 in our data, and Houston (TX) ranks 8 in theirs.

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.[27]

USDA Natural Amenities Data We use the natural amenities scale provided by the US Department of Agriculture. This scale is "a measure of the physical characteristics of a county area that enhance the location as a place to live." The measure is constructed as a composite of local temperatures, hours of sun, humidity, topography, and water area. We aggregate the measure to the CZ-level by taking the population-weighted average over a CZ's counties.

Various COVID Case Data We use data on monthly COVID cases by ZIP codes for Atlanta, Boston, Chicago, New York City, Philadelphia, San Francisco, and Santa Clara. Only few cities provide a history of COVID cases at the ZIP code level. As a robustness check, we use this limited sub-sample to show that our results are not driven by differential exposure to COVID infections of ZIP codes within cities. We thank Caitlin Gorback and Steve Redding for generously sharing their replication data (Glaeser et al., 2020).

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.[28]

We compute the average change in the ZORI index relative to January 2020 for all ZIP Codes within a county.

B. Additional Exhibits

B.1. Remote Work Potential and Population Density: The Role of Industrial Structure

Table A.1 shows that the relationship between remote work potential and population density in the cross-section of commuting zones is almost entirely due to differences in the fraction of local workers employed in business service industries.

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 improves the fit somewhat, by going from 1 to 19 industry shares. 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.[29]

SSS jobs tend to be done by highly-skilled workers (see Eckert et al., 2020). In Table A.7, we replicate Table A.1 but replace SSS employment share with the college share of employment. The college share alone also explains a high fraction of the remote work potential, as the SSS share and the college share are highly correlated at the local level. However, it is the nature of the job itself which fundamentally determines whether the job can be done remotely, not the college status of the person doing the job. For example, Dingel and Neiman (2020) find that only 5% of healthcare practitioners, a highly-skilled worker group, can work from home. Indeed, in Figure A.5, we show that throughout this period, both college and non-college workers in SSS saw higher rates of working from home than college workers outside SSS. For these reasons, we focus on the industrial determinants of remote work throughout the paper.[30]

[27] "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.

[28] For more details on the methodology employed by Zillow, see https://www.zillow.com/research/methodology-zori-repeat-rent-27\,092/.

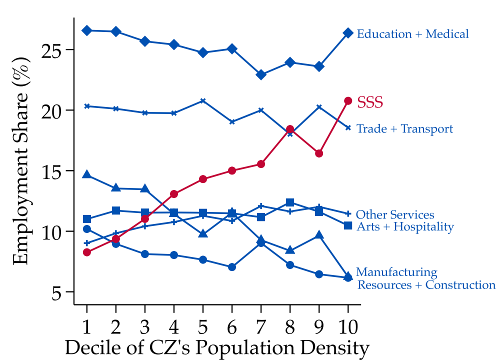
[29] In other words, occupational composition is almost completely accounted for by variation in industrial composition. The within-industry spatial variation in occupations (at least in terms of scope for remote work) is very small.

[30] In addition, policy makers may find it easier to target industrial structure if they want to make big cities more resilient to remote work shocks.

Table A.1
Remote Work Potential And Industrial Structure

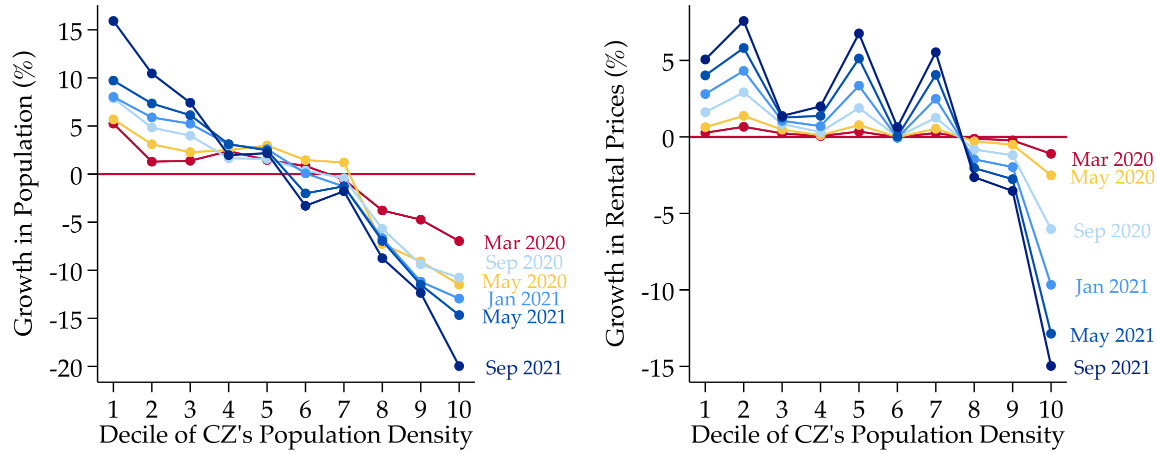
	Share of Local Jobs That Can Be Done Remotely				
	(1)	(2)	(3)	(4)	(5)
Log Population Density	0.020***	0.003***	0.004***	0.001	0.002
	(0.002)	(0.001)	(0.001)	(0.001)	(0.004)
SSS Employment Share		1.293***		0.645***	1.284***
		(0.039)		(0.059)	(0.068)
Log Population Density × SSS Employment Share					0.011
					(0.047)
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 to 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 et al., 2020). College employment share is the fraction of workers with at least a college degree in a given commuting zone. Log population density is standardized to have zero mean and unit variance. 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.



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 US 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.

Fig. A.1 Industry Employment Across Cities



Notes: For the left panel, we use data from SafeGraph 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. To isolate price increases above and beyond national rental price inflation, 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. 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 US 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.

Fig. A.2 Population Growth and Rental Home Prices

Table A.2
The Impact of the Remote Work Shock on City Neighborhoods

	Growth in				
	Population (SafeGraph)	Rental Prices (Zillow)	Stay at Home (Facebook)	Foot Traffic (SafeGraph)	Consumer Spending (Affinity)
SSS Employment Share × February 2020	−32.579***	−3.342***		3.139	1.616***
	(3.974)	(0.271)		(4.762)	(0.000)
March 2020	−10.892**	−6.700***	390.778***	−77.824***	−34.220***
	(4.492)				
		(0.538)	(62.819)	(6.435)	(0.000)
May 2020	−44.223***	−14.136***	390.113***	−169.835***	−115.319***
	(6.592)	(1.245)	(59.098)	(11.685)	(0.000)
September 2020	−23.900***	−30.322***	208.872***	−115.389***	−72.047***
	(6.617)	(2.764)	(28.369)	(11.828)	(0.000)
January 2021	−13.655**	−38.905***	225.662***	−82.291***	−88.565***
	(5.707)	(3.798)	(28.956)	(10.607)	(0.000)
May 2021	−21.648***	−38.039***	112.539***	−165.150***	−55.100***
	(8.034)	(5.655)	(23.662)	(23.772)	(0.000)
September 2021	−85.231***	−35.824***	42.727**	−189.984***	−55.201***
	(9.270)	(7.777)	(20.119)	(31.363)	(0.000)
CZ × Month-FE	Yes	Yes	Yes	Yes	Yes
State-FE	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.082	0.823	0.944	0.018	0.758
Level of Observation	ZIP	ZIP	County	ZIP	County
Observations	774,501	41,791	46,082	659,102	35,421

Notes: We combine the data sets of SafeGraph, 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 and state 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 et al., 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 Excluding New York City and San Francisco

	Percentage Growth Since January 2020				
	Population (SafeGraph)	Rental Prices (Zillow)	Stay at Home (Facebook)	Foot Traffic (SafeGraph)	Consumer Spending (Affinity)
SSS Employment Share × February 2020	−30.250***	−3.212***		0.966	−2.369
	(3.971)	(0.317)		(5.579)	(8.133)
March 2020	−10.632**	−6.440***	449.558***	−84.276***	−29.022***
	(5.056)	(0.621)	(47.803)	(6.839)	(9.920)
May 2020	−39.100***	−13.480***	444.302***	−182.663***	−106.459***
	(5.931)	(1.470)	(44.384)	(11.541)	(15.672)
September 2020	−21.720***	−28.641***	226.128***	−123.488***	−62.340***
	(6.583)	(3.282)	(30.947)	(10.738)	(16.390)
January 2021	−12.595**	−37.630***	248.077***	−87.039***	−76.473***
	(6.097)	(4.463)	(33.283)	(8.728)	(19.131)
May 2021	−18.471**	−38.040***	125.899***	−184.382***	−68.191***
	(8.264)	(6.285)	(28.649)	(22.302)	(21.571)
September 2021	−83.334***	−37.115***	52.129**	−225.702***	−51.535**
	(9.948)	(8.239)	(25.455)	(25.833)	(26.150)
CZ × Month-FE	Yes	Yes	Yes	Yes	Yes
State-FE	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.070	0.826	0.945	0.017	0.753
Level of Observation	ZIP	ZIP	County	ZIP	County
Observations	752,871	38,285	45,502	638,523	34,863

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, 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 and state 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 et al., 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 Measuring SSS Employment Shares by Place of Work

	Percentage Growth in Foot Traffic Since Jan 2020 (SafeGraph)
SSS Employment Share × February 2020	3.431**
	(1.604)
March 2020	−25.145***
	(2.031)
May 2020	−45.063***
	(4.437)
September 2020	−43.928***
	(8.632)
January 2021	−33.419***
	(2.930)
May 2021	−53.334***
	(6.037)
September 2021	−30.768
	(29.087)
CZ × Month-FE	Yes
State-FE	Yes
Adjusted R-squared	0.021
Level of Observation	ZIP
Observations	542,929

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, 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 and state 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 et al., 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 Local COVID Cases

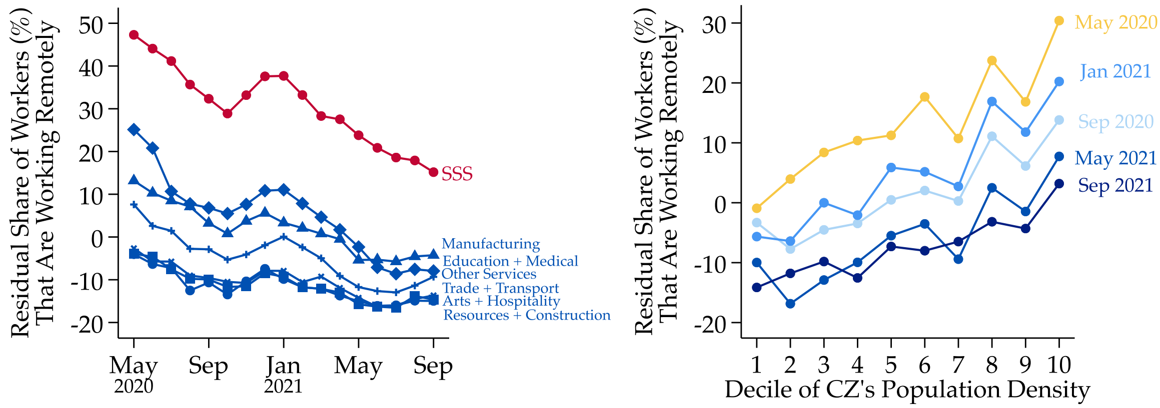
	Percentage Growth Since January 2020				
	Population (SafeGraph)	Rental Prices (Zillow)	Stay at Home (Facebook)	Foot Traffic (SafeGraph)	Consumer Spending (Affinity)
SSS Employment Share × February 2020	−53.741***	−3.260***		9.863	12.428***
	(8.192)	(0.259)		(9.137)	(0.000)
March 2020	−11.571**	−6.525***	389.916***	−70.455***	−34.157***
	(4.545)	(0.570)	(65.168)	(6.730)	(0.000)
May 2020	−45.612***	−13.978***	394.125***	−164.337***	−115.176***
	(6.263)	(1.253)	(60.601)	(11.419)	(0.000)
September 2020	−25.126***	−30.143***	213.192***	−110.427***	−71.540***
	(6.177)	(2.737)	(28.181)	(12.683)	(0.000)
January 2021	−13.754**	−37.440***	235.258***	−76.275***	−83.761***
	(5.541)	(3.775)	(30.492)	(12.003)	(0.000)
May 2021	−22.841***	−37.684***	117.274***	−159.982***	−54.311***
	(7.828)	(5.677)	(23.394)	(24.484)	(0.000)
September 2021	−84.914***	−34.707***	54.641**	−183.034***	−48.554***
	(9.074)	(7.813)	(21.825)	(32.178)	(0.000)
Per-capita COVID cases	Yes	Yes	Yes	Yes	Yes
CZ × Month-FE	Yes	Yes	Yes	Yes	Yes
State-FE	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.083	0.817	0.937	0.018	0.760
Level of Observation	ZIP	ZIP	County	ZIP	County
Observations	692,502	38,732	42,845	590,994	31,711

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, 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 and state 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 et al., 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.6
The Impact of the Remote Work Shock on City Neighborhoods Including Control for Neighborhood Population Density

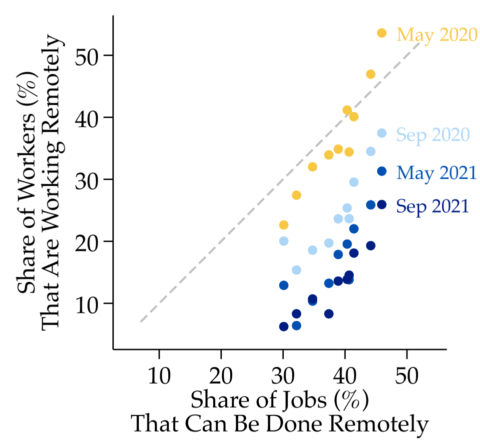
	Percentage Growth Since January 2020				
	Population (SafeGraph)	Rental Prices (Zillow)	Stay at Home (Facebook)	Foot Traffic (SafeGraph)	Consumer Spending (Affinity)
SSS Employment Share × February 2020	−32.579***	−3.323***		3.156	19.734
	(3.974)	(0.282)		(4.764)	(19.305)
March 2020	−10.892**	−6.689***	357.117***	−77.808***	−30.039**
	(4.492)	(0.544)	(60.363)	(6.434)	(11.728)
May 2020	−44.223***	−14.141***	361.047***	−169.864***	−111.176***
	(6.592)	(1.245)	(55.687)	(11.703)	(17.722)
September 2020	−23.900***	−30.283***	179.936***	−115.486***	−67.946***
	(6.617)	(2.760)	(25.776)	(11.806)	(16.541)
January 2021	−13.655**	−38.838***	196.663***	−82.307***	−84.464***
	(5.707)	(3.807)	(25.325)	(10.617)	(21.406)
May 2021	−21.648***	−37.997***	83.464***	−165.163***	−50.999*
	(8.034)	(5.643)	(22.041)	(23.780)	(28.679)
September 2021	−85.231***	−35.834***	13.589	−189.980***	−52.150**
	(9.270)	(7.748)	(19.121)	(31.367)	(24.428)
Population Density	Yes	Yes	Yes	Yes	Yes
CZ × Month-FE	Yes	Yes	Yes	Yes	Yes
State-FE	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.086	0.839	0.938	0.019	0.760
Level of Observation	ZIP	ZIP	County	ZIP	County
Observations	774,501	41,791	42,845	659,102	31,711

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, 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 and state 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 et al., 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.



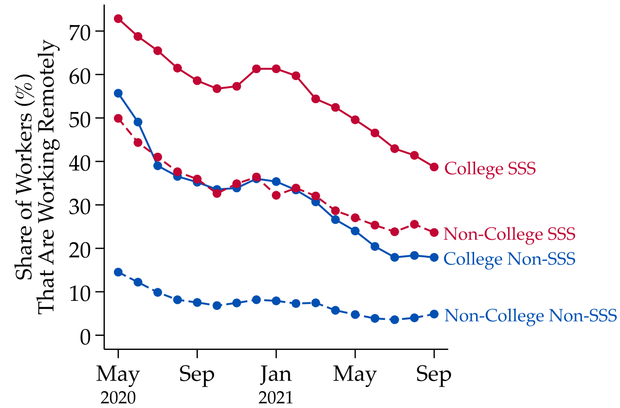
Notes: This Figure replicates Figure 2, but residualizes remote work with average per-capita COVID cases within each month and density decile or industry. We use data on COVID cases by county from the New York Times. We use data on the fraction of people working remotely in each industry from the CPS's 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 right 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 US 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.

Fig. A.3 Remote Work During the Pandemic



Notes: This figure relates commuting zones' remote work potential to actual remote work. Each dot represents a CZ population density decile in a given month. For remote work potential, 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). For actual remote work, 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. 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.

Fig. A.4 Remote Work During the Pandemic



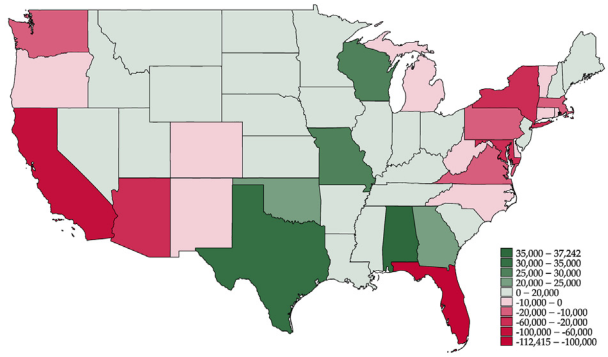
Notes: This Figure replicates the right panel of Figure 2, but splits workers into SSS and non-SSS workers with and without at least a college degree. We use data on the fraction of people working remotely in each industry from the CPS's supplemental COVID-19 measures. The variable "covidtelew," reflects whether or not a person has done telework or work-from-home in the last four weeks because of the COVID-19 pandemic. We drop data for Alaska, Hawaii, and Washington, D.C., from our sample.

Fig. A.5 Remote Work During the Pandemic

Table A.7
Remote Work Potential And College Shares

	Share of Local Jobs That Can Be Done Remotely		
	(1)	(2)	(3)
Log Population Density	0.001***	−0.008***	0.000
	(0.000)	(0.002)	(0.000)
College Employment Share	0.632***	0.454***	0.464***
	(0.022)	(0.055)	(0.037)
Log Population Density × College Employment Share		0.036***	
		(0.009)	
SSS Employment Share			0.905***
			(0.095)
College Employment Share × SSS Employment Share			−0.797***
			(0.192)
Adjusted R-squared	0.832	0.842	0.889
Observations	722	722	722

Notes: This Table replicates Table A.1, showing additional results for college employment shares. We use occupation-level employment data from the pooled American Community Survey from 2014 to 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 et al., 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.



Notes: This Figure computes the change in states' population from February 2020 to August 2020. We compute population changes based on data from SafeGraph and compare our estimates to those obtained from USPS data on address changes (compare to the map in https://www.mymove.com/moving/covid-19/coronavirus-moving-trends/). While the SafeGraph data captures both temporary and permanent moves, the USPS data only captures reported permanent moves. Despite the different natures of the data sets, the patterns are broadly consistent. We drop data for Alaska, Hawaii, and Washington, D.C., from our sample.

Fig. A.6 Population Change by State

Table A.8
The Impact of the Remote Work Shock on City Neighborhoods Including Control for Neighborhood COVID Cases

	Growth in					
	Population (SafeGraph)	Rental Prices (Zillow)	Foot Traffic (SafeGraph)	Population (SafeGraph)	Rental Prices (Zillow)	Foot Traffic (SafeGraph)
SSS Employment Share × May 2020	−56.064	8.761	−168.917***	−41.615	11.649	−168.744***
	(54.181)	(10.753)	(40.333)	(53.271)	(9.355)	(41.507)
September 2020	13.549	−9.271	−131.207***	15.324	−8.871	−131.177***
	(46.805)	(10.066)	(29.502)	(47.605)	(9.349)	(29.785)
January 2021	27.765	−15.001*	−100.814**	69.088	−8.998	−100.400**
	(65.270)	(7.804)	(41.075)	(95.303)	(5.582)	(45.668)
May 2021	14.152	−8.439**	−105.274***	20.491	−6.522**	−105.188***
	(46.064)	(4.207)	(15.697)	(50.403)	(3.135)	(16.223)
August 2021	7.292**	−2.397**	−73.877*	8.251***	−2.561***	−73.869*
	(3.275)	(1.017)	(40.676)	(2.373)	(0.887)	(40.590)
Per-capita COVID cases	No	No	No	Yes	Yes	Yes
CZ × Month-FE	Yes	Yes	Yes	Yes	Yes	Yes
State-FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.050	0.658	0.080	0.053	0.828	0.080
Level of Observation	ZIP	ZIP	ZIP	ZIP	ZIP	ZIP
Observations	5543	2468	5494	5543	2468	5494

Notes: This Table replicates Table 2, but controls for monthly COVID cases per capita at the ZIP code level. We obtain data on COVID cases from the local government websites by New York, Chicago, San Francisco, and Santa Clara between May 2020 and August 2021. For other cities, we were not able to obtain panel data on COVID cases at the ZIP code-level. We combine the data sets of SafeGraph and Zillow to measure local outcomes at the ZIP-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 and state 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 et al., 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.

C. *A Simple Theoretical Framework*

In this section, we modify the classic Rosen-Roback model to formalize our mechanism.

Setup The economy consists of a discrete set of locations indexed by $r = 1, \ldots, R$. In each location there are two sectors. Sector A employs workers who produce a homogeneous, traded good whose price serves as the numeraire. Sector B employs workers who produce a non-tradable good with price p_r. Both sectors have linear production technologies that only use labor. Locations differ in their productivity for sector A, Z_r; productivity in sector B is the same for all locations.

Workers cannot choose their sector so that we refer to workers of type A and workers of type B. We denote the number of workers of type A and B in location r by L_{rA} and L_{rB}, respectively, and their total number in the economy by $\overline{L}_A$ and $\overline{L}_B$. Locations differ in amenities for traded good workers: $A_r = \overline{A} L_{rA}^{-\rho}$; amenities for consumer service workers are the same in all locations. All workers spend a fraction α on the local good and the rest on the tradable good. Workers in both sectors are freely mobile.

Equilibrium In spatial equilibrium, the fraction of tradable workers in each location is given by:

$$L_{rA} = \frac{[\overline{A_r} Z_r / p_r]^{1/\rho}}{\sum_r [\overline{A_r} Z_r / p_r]^{1/\rho}} \overline{L}_A \equiv Z_r^{1/\rho} \overline{A_r}^{1/\rho} \overline{L}_A \Omega_A,$$

where we used the fact that wages of type A workers are equal to their marginal product (Z_r), and that $p_r = w_{rB} = \overline{w}_B$ in spatial equilibrium. Ω_A is a general equilibrium object.

The total payroll, i.e., economic size, of the local consumer service sector then is:

$$w_{rB} L_{rB} = \alpha \left[w_{rA} L_{rA} + w_{rB} L_{rB} \right]$$

We can rewrite this as

$$w_{rB} L_{rB} = \frac{\alpha}{(1-\alpha)} w_{rA} L_{rA} \Rightarrow L_{rB} = Z_r^{1+1/\rho} \overline{A_r}^{1/\rho} \overline{L}_B \Omega_B$$

where we used the fact that wages of type A workers are equal to their marginal product (Z_r), and that $p_r = w_{rB} = \overline{w}_B$ in spatial equilibrium. Ω_B is a general equilibrium object.

In summary, in equilibrium, type A workers choose locations in which productivity and amenity for type A workers are high. Since their output is tradable, the size of the local market for their good is irrelevant. Type B workers on the other hand choose locations in which overall spending of type A workers is high, i.e., locations in which in which productivity and amenity for type A workers are high. The reason type B workers seek out such locations is because the market for their non-tradable services is large in these locations. This shows the sense in which, within a location, non-tradable service workers depend on tradable sector workers for their livelihood.

A Remote Work Shock in the Model We think about a remote work shock as an equalization of tradable good productivity across locations so that in a remote work world $Z'_r = \overline{Z} > 0$: it is no longer necessary to be in a certain location to access the local production technology. Comparing the pre-shock and post-shock period, we obtain $d \log Z_r = \log \overline{Z} - \log Z_r$.[31]

We are interested in the direct effect of a remote work shock, prior to adjustment to a new steady state. Since our model is not dynamic, we need to make ad-hoc assumptions about the adjustments workers can make to a sudden shock. We assume that type A workers can move in response to a remote work shock, whereas type B workers cannot, to capture that fact that consumer service workers are less responsive to wage changes (see Notowidigdo, 2020). It is easy to amend our framework to allow both types of workers to change location at different speeds.

We now establish the effect of a sudden remote work shock in our model.

Proposition 1. *If tradable worker productivity is equalized across regions, relative non-tradable worker wages of two regions r and r′ change as follows:*

$$d \log w_{rB} / w_{r'B} = (1 + 1/\rho) \log Z_{r'} / Z_r$$

The proposition shows that for any two regions, the region with the higher initial wage for tradable service workers sees a larger decline in demand for non-tradable service workers, and a larger decline in their wages. Since big cities pay higher wages than small cities, an empirical version of our model makes two testable predictions:

1. Big cities should see more outflows of tradable service workers as remote work becomes possible than smaller cities.
2. Average wages of non-tradable service workers in big cities should fall more compared to non-tradable service workers in smaller cities.

The Pandemic in the Model During the recent pandemic, going to work became dangerous (Glaeser et al., 2020) so that workers who could, started working from home. As such, the pandemic provided a remote-work shock, an equalization of productivities across locations: suddenly New York workers no longer had to be in New York to access New York productivity. Consequently, the pandemic allows us to test the two predictions of our model for the immediate impact of remote work.

Many authors have argued that the pandemic had an additional effect: as workers started to stay inside their homes and stopped interacting with local amenities it was as if amenities across locations were equalized. We can hence think of the pandemic as additionally reducing tradable sector workers' amenities, so that $A_r = \overline{A} > 0$, so that they become more similar to other locations. But then the pandemic induces the following shock to location r tradable worker productivity: $d \log A_r = \log \overline{A} - \log A_r$.

The following proposition establishes the effect of an equalization of amenities across locations.

Proposition 2. *If tradable worker amenities are equalized across regions, relative non-tradable worker wages of two regions r and r′ change as follows:*

$$d \log w_{rB} / w_{r'B} = (1/\rho) \log A_{r'} / A_r$$

The proposition suggests that an equalization of amenities has a similar effect of an equalization of productivities: it makes tradable service workers leave location with high amenities. Since in the cross-section of US cities, the largest cities are also generally the most attractive, the propositions imply that the pandemic lowers wages for consumer service workers in big cities. Importantly, workers are only able to leave locations due to amenity equalization if they can work remotely. As a result, some of the outflows we observed are only indirectly due to remote work and should reverse once big city amenities can again be used.

Hence, our model generates an additional prediction for a remote work shock during a pandemic which forces people to stay at home and forgo amenity use: controlling for the initial share of tradable workers, higher amenities should beget even larger outflows of tradable service workers and larger reductions of non-tradable service workers' wages.

3. All else equal, effects (1.) and (2.) above should be stronger in cities with higher pre-pandemic amenities.

[31] For our mechanism it is irrelevant whether all locations inherit the productivity of the most or least productive location in a remote work world.

Note that non-tradable workers are more affected by the equalization of productivities than by the equalization of amenities. When productivities are equalized, non-tradable service workers' wages are hurt both due to relative declines in big city tradable workers' wages and a reduction in their numbers. With only amenities equalized, non-tradable service worker wages are hurt only due to a reduction in tradable service workers numbers, but not their wages. Since the direct effect only works through labor supply in this case, the coefficient on amenity changes is smaller than that in front of productivity changes.

A Suggestive Test of Prediction 3 We can conduct a simple test of Prediction 3. above by taking our simple framework to the data on employment and wages across space during this period.

We first need to calibrate a structural parameter, the disamenity term ρ. This parameter controls how utility diminishes the greater the local population. It directly maps into the local labor supply elasticity, holding all other wages and amenity terms constant, which is given by $1/\rho$. We choose this to match the labor supply elasticity of those with college degree in Diamond (2016), which is 5.5.

We next map the model to the data by assuming that workers in the A sector correspond to workers in the SSS industries (NAICS 51,52, 54 and 55). We obtain total employmen in these industries in each commuting zone from the American Community Survey (ACS), giving us measures of $L_{r,\text{SSS}}$ and $L_{r,\text{Non-SSS}}$.

We can then solve for the amenities (up to scale) by solving for $\overline{A}_r$ from

$$L_{rA} = w_{r,SSS}^{1/\rho}\overline{A}_r^{1/\rho},$$

Note that in this simple exercise, amenities are highly correlated with total population size, and so the results must be interpreted with caution. Table A.9 presents the results of regressing commuting zone population growth between January 2020 and August 2021 on a commuting zone's derived amenity score and its pre-pandemic SSS employment share. Throughout all specifications, the coefficient on the SSS employment share of a commuting zone is negative reflecting our mechanism: as SSS workers moved to remote work, they left their original cities of residence.

In line with Prediction 3 of the model, the coefficient on the amenity score is negative, too: conditional on an initial SSS employment share, cities with higher amenities saw even more negative population growth. This finding is robust to controlling for an interaction (Column 3), to separately controlling for population density (Column 4), and controlling for outflows in the initial phase of the pandemic (January to June 2020).

In Column 4, we use an alternative amenity score provided by the United States Department of Agriculture. The "USDA Natural Amenities Data" is an index of natural amenities across US cities. We discuss this data in more detail in Appendix A. Reassuringly, the coefficient on the natural amenity score is also negative, again confirming the prediction of the model: if workers value amenities less because "being outside" entails the risk of infection, locations with high initial amenities should see larger outflows.

If the pandemic recedes, it will be interesting to see whether workers return to high amenity locations at a faster rate, too. In a recent paper, Ahlfeldt et al. (2020) show how to infer such quality of life residuals in a more rigorous way, taking into account dynamic decisions of workers and not assuming an economy in steady state. Studying population growth across cities in the aftermath of COVID-19 using more rigorously-derived quality of life residuals is an interesting avenue for future research.

Table A.9
Population Growth and Amenities

	Population Growth January 2020 to August 2021				
	(1)	(2)	(3)	(4)	(5)
Amenity Score	−0.876	−14.844	8.630***		−1.279
	(4.561)	(9.084)	(3.138)		(2.111)
SSS Employment Share	−163.651***	242.284	−68.425***	−153.453***	−102.754***
	(20.031)	(334.258)	(18.413)	(16.365)	(12.695)
Amenity Score × SSS Employment Share		105.384			
		(86.736)			
Log Population Density			−5.231***		
			(0.588)		
Natural Amenity Score				−1.180***	
				(0.222)	
Cumulative Population Outflow (%) from January to June 2020					0.655***
					(0.067)
Adjusted R-squared	0.419	0.423	0.596	0.528	0.650
Observations	722	722	722	722	722

Notes: This Table shows how population growth (%) between January 2020 and August 2021 differed across Commuting Zones (CZs) and their amenity scores. As the outcome, we use data from SafeGraph to construct a measure of local population growth on the CZ-level. Amenity scores reflect the log-transformed parameter A_r. We use data on the population, employment, and wages by sector and CZ from the 2014-2018 American Community Survey (ACS). SSS employment share is the fraction of local employment in a commuting zone in NAICS industries 51, 52, 54, or 55 (see Eckert et al., 2020). 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. Natural amenity scores are a composite measure determined by local temperatures, hours of sun, humidity, topographic variation, and water area. from the US Department of Agriculture. We drop data for Alaska, Hawaii, and Washington, D.C., from our sample. 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.

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