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## **The Impact of Remote Work on Local Employment, Business Relocation, and Local Home Costs**

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# The impact of remote work on local employment, business relocation, and local home costs

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## **Abstract**

We first impute teleworking take-up rates for the universe of business establishments in the U.S for the period immediately preceding the pandemic and for the summer of 2021. Using establishment address and residence by occupation, we estimate the change in foot traffic inflow for every Census tract. We document the consequent effects of changes in foot traffic on local employment by sector. The negative employment effect is especially strong for employment in accommodation and food services. Finally, we use the telework take-up rates and foot traffic measures to show the impacts on businesses downsizing, relocating, and local rent and home prices.

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# 1 Introduction

COVID-19 has triggered a major change in where workers perform their jobs. The rise of the internet and the improvement in online access during the 21st century has made working from home possible for an increasing share of the workforce. Prior to the pandemic, working from home had been increasing slowly, but the number of people working from home exploded during the pandemic. A set of estimates cited by Barrero et al. (2021) indicates that the percentage of paid workhours rose from 5 percent before the pandemic to roughly 50 percent in April 2020. In a similar vein, the estimates by Dey et al. (2020) using the American Time Use Survey and the 1979 cohort of the National Longitudinal Survey of Youth (NLSY79) imply that prior to the pandemic about 12 percent of workers teleworked one or more days per week. In comparison, analysis of a COVID-19 supplement of the 1997 cohort of the National Longitudinal Survey of Youth (NLSY97) fielded from February 2021 to May 2021 indicates that on average 38 percent of workers worked from home one day or more.<sup>1</sup>

As the pandemic has receded, teleworking rates have dropped from their peak in the spring of 2020. By way of illustration, CPS estimates indicate that in May 2020, 35.4 percent of workers worked at home for pay some time in the previous four weeks because of the COVID-19 pandemic. By February 2022, this figure had dropped to 13 percent.<sup>2</sup> However, there is little doubt that work from home rates will remain substantially above their levels prior to the pandemic. As noted by Barrero et al. (2021), workers' work from home experiences have often been better than expected, there have been new investments in physical and human capital that enable work from home, and there is now a diminished stigma associated with working from home.

Much of the benefit from working at home stems from the reduction in the monetary and especially the time cost of commuting. This has important spillover effects on local labor and housing markets. Casual observation indicates that central cities were severely impacted by the pandemic, as the loss of commuters meant a substantial reduction in the demand for local services. Evidence in support of this is provided by Althoff et al. (2022) who use the American Community Survey to calculate the share of workers residing in each zip code who work in Information, Finance and Insurance, Professional Services, and Management of Companies. These industries, which for shorthand are referred to by the authors as "Skilled Scalable Services" (SSS) consist of occupations having a high potential for working at home, as measured by Dingel and Neiman (2020) using O\*NET data. Althoff et al. find that areas with a high proportion of workers in SSS industries experienced significant declines in visits to local consumer establishments, such as hotels, restaurants, bars, and barbers during the pandemic. The change in foot traffic was accompanied by a change in consumer spending. Rents also fell by a greater amount in zip codes with a high proportion of workers in SSS industries.

The fact that jobs that are well suited for teleworking tend to be heavily concentrated in dense, central cities has implications for rents and housing prices. Employers whose workers work from home more often may be able to reduce their office space, which would put downward pressure on rents and housing prices. A reduction in the profitability of establishments catering to commuters is another potential source of downward pressure on rents and housing costs in central cities. In addition, increased teleworking affects households' residential decisions. As noted by Brueckner et al. (2021) and others, workers who are commuting

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<sup>1</sup>Similarly, in a recent paper, Brynjolfsson et al. (2022) estimate that in Oct. 2020, 31.6% of continuously employed workers always worked from home and 22.8% sometimes or rarely worked at home. Bick et al. (2021) find 33% of employment teleworked at least some of the time as of December 2020. Dalton and Groen (2022), using the 2021 Business Response Survey, find 22% of jobs telework at least some of the time as of Summer 2021.

<sup>2</sup>Note that given the wording of the CPS question, it is difficult to compare these estimates with those cited above.

less frequently find it attractive to move toward more outlying locations away from the city center where home prices and rents are lower.<sup>3</sup> Several authors have documented effects of the pandemic on local rents and housing prices. Rosenthal et al. (2022) find that the pandemic has led to a substantial fall in the commercial rent gradient in large dense cities that are heavily dependent on transit. Ramani and Bloom (2021) find a “donut effect” in which rents and home values fall in the large central cities and rise in their low-density suburbs.<sup>4</sup> Analyzing change of address forms, they find net outflows of population and business establishments from central business districts during the pandemic. Gupta et al. (2022) estimate a 35% decline in New York City office values in 2020 and 28% in the longer run. In contrast, Delventhal and Parkhomenko (2022) argue that “the impact of remote work may be large, but is unlikely to be catastrophic” and Mondragon and Wieland (2022) estimate that the shift to remote work explains over half of the 23.8 percent national home price increase from December 2019 to November 2021.

In this paper, we combine five different data sets to further analyze the effects of teleworking. The first of these is the Business Response Survey (BRS). The BRS is a new Bureau of Labor Statistics (BLS) survey fielded from July 27 through September 30, 2021 that contains a series of questions about firms’ behavior during the pandemic and their expectations about the future. The other data sets that we use are the Occupational Employment and Wage Statistics (OEWS), the Quarterly Census of Employment and Wages (QCEW), the American Community Survey (ACS), and Zillow.

We expand on the existing literature in several important ways. Much of the literature analyzing teleworking does not have actual measures of teleworking measures but instead uses the Dingel-Nieman O\*Net based measures to identify occupations, industries, and geographical areas that have a high potential for teleworking, treating each occupation as either “teleworkable” or not.<sup>5</sup> In contrast, we utilize information in the BRS about firms’ actual teleworking practices in order to measure take-up of telework within occupations. Combining the BRS, the OEWS, and the QCEW, we impute teleworking take-up rates for the universe of business establishments in the U.S for the summer of 2021, for the period immediately preceding the pandemic, and (using establishments’ responses to a question about their expectations about future teleworking) for the period following the pandemic.<sup>6</sup> These estimates also produce telework take-up rates for each detailed occupation in the Standard Occupational Classification (SOC) system.

In addition to information about teleworking, the BRS also contains information on whether establishments have relocated or downsized since the start of the pandemic and whether they expect to in the future. Having instituted higher teleworking, firms may find it attractive to relocate and/or downsize. We predict a firm’s decision to relocate or downsize on the basis of whether teleworking by its employees has increased. And using the OEWS and QCEW, we form predictions for the entire universe of establishments.

Increased teleworking may have substantial effects on a local economy through its effect on foot traffic. Two competing forces are at work. A reduction in local foot traffic when workers who previously commuted into an area instead work at home is countered by an increase in local foot traffic when workers stop commuting out of the area. Using information in the ACS on workers’ occupations and places of residence

<sup>3</sup>Delventhal and Parkhomenko (2022), Delventhal et al. (2022), and Liu and Su (2021) build spatial models to analyze these effects. Delventhal and Parkhomenko (2022)’s results indicate that teleworking causes population in the average big metro area to fall by about 2.5%. Analyzing job postings in Burning Glass, Liu and Su (2021) find that occupations in which work from home is greatest experienced a strong decrease in the urban wage premium.

<sup>4</sup>Similarly, Liu and Su (2021) find that the pandemic has led to a shift in housing demand away from high population density downtown neighborhoods toward lower density neighborhoods further from the central city.

<sup>5</sup>For example, see Mongey et al. (2021). Dey et al. (2021) apply the Dingel-Nieman framework in their analysis of U.S. teleworking rates using the Current Population Survey. Gottlieb et al. (2020) apply the Dingel-Nieman framework to analyze the potential to work from home in developing countries.

<sup>6</sup>Brynjolfsson et al. (2022) compare work from home rates in an online survey with those predicted by Dingel and Neiman. Bartik et al. (2020) relate estimates from firm-level surveys to the Dingel and Neiman predictions.

together with our estimates of teleworking take-up rates by occupation, we estimate telework rates by place of residence. As noted above, we also are able to obtain teleworking estimates for the universe of establishments. Combining these estimates of teleworking by place of work with the estimates by place of residence, we estimate the change in net traffic inflow for every Census tract. Armed with these estimates and the QCEW, we then estimate the consequent effects on local employment in the various industries. We find that accommodation and food services, in particular, are negatively impacted by reduced foot traffic within a Census tract.

We conclude our analysis by bringing in Zillow data to analyze the effect that the changes brought on by increased working at home has on local rents and home prices. The key explanatory variables in the estimated equations are predictions by zip code for firm relocations, firm downsizing, and the change in net foot traffic inflow.

Section 2 describes the key BLS data sets used in the analysis. Section 3.1 derives teleworking take-up rates for nearly all occupations and establishments in the economy. Sections 3.2 and 3.3 looks at the effect of increased teleworking on local employment and housing rents. Concluding remarks are presented in Section 4.

## 2 Bureau of Labor Statistics Data

As discussed above, in this paper we combine several datasets to obtain estimates of teleworking take-up rates and the consequent effects on foot traffic during the pandemic. Armed with the estimates of the changes in foot traffic, we then analyze the resultant effects on economic activity.

An increase in the number of individuals working from home as opposed to visiting the location of their employer on a daily basis results in a reduction in foot traffic in the vicinity of employers, but an increase in foot traffic where individuals live. Our analysis of the change in foot traffic by geographical area thus utilizes information on the take-up of telework by occupation as well as on where workers in various occupations live and work. The first step in our analysis involves estimating teleworking take-up rates by occupation. We obtain these estimates using three data sets: the Business Response Survey (BRS), Occupational Employment and Wage Statistics (OEWS), and the Quarterly Census of Employment and Wages (QCEW).

The Business Response Survey was created in response to the pandemic in 2020. There have been two iterations of the Internet-collected survey in Summer 2020 and 2021. We use responses to the Summer 2021 survey. The responses come from a nationally representative sample of over 300,000 private sector employers that contribute into the Unemployment Insurance system. The survey asked a variety of questions, most relevantly about telework and changes to the physical footprint of the business location. The sample for the BRS comes from the QCEW, which is the universe of all employers in the United States that pay into the Unemployment Insurance, which covers over 95% of all employment in the United States. The QCEW contains each establishment's historical reported monthly employment and quarterly wages as well as detailed location information.

The BRS contains a sequence of questions asking the establishment what percentage of their workforce teleworks full-time and what percentage teleworks some of the time. As is well known, the likelihood that workers telework depends crucially on their occupation. The BRS does not contain information on occupation, but we can impute the occupational composition of nearly all establishments in the U.S. using information in the 2016-2018 OEWS microdata and the QCEW.

The occupation data come from the BLS's Occupational Employment and Wage Statistics (OEWS) survey, which is a semi-annual mail survey that samples approximately 200,000 establishments in May and November of each year. The OEWS provides much more occupational detail than most other surveys that include information about occupation. The survey covers all workers, both full time and part time, in private non-agricultural industries. The survey instrument asks establishments to provide what amounts to a complete payroll record for the pay period that includes the 12th of the sample month. Respondents report occupational wage information for each occupation by recording the number of employees in each of 12 wage intervals.<sup>7</sup> The OEWS survey uses the Office of Management and Budget's (OMB) occupational classification system, the Standard Occupational Classification (SOC), to categorize workers into around 800 detailed occupations.<sup>8</sup>

The OEWS sampling and weighting methods guarantee that total weighted employment equals QCEW employment, but there is nothing in the methods to guarantee that the implied number of establishments equals the number of establishments on the frame. This makes it difficult to develop statistics at the establishment level. Therefore, any analysis that attempts to measure establishment-specific effects will have to address this feature of the OEWS weighting scheme. As an alternative to reweighting the data, we use a research dataset that was created using a modified version of the imputation approach developed by Dey et al. (2019).

Dey et al. (2019) impute data for the entire QCEW. For each reference year, they use the same dating convention as for the official OEWS release (that is, May of the reference year combined with the five previous panels). For each observation in the QCEW, Dey et al. identify 5–10 donor observations based on the characteristics of the establishments. The characteristics include employment, industry (6-digit NAICS), ownership, metropolitan statistical area (MSA), and the amount of time between reference periods of the observations. Donor establishments are evaluated on each attribute and weights are assigned based on closeness to the recipient on that attribute. The recipient's employment in each occupation is a weighted average of the donor establishments, whose weights are rescaled to sum to one. Wages are determined similarly but are also adjusted for differences in wages by area and wage growth by area and industry.<sup>9</sup>

The Dey et al. (2019) approach was designed as a replacement for the previous estimation methodology for generating official estimates; OEWS began using the new methodology for May 2021 estimates. The main advantage of this approach is that every establishment in the QCEW is represented and has an establishment weight of one. The disadvantage for our purposes is that the staffing pattern for an establishment is an average of similar establishments. This makes sense for constructing aggregate estimates, but not for analyzing distributions. We therefore develop a dataset that incorporates two key modifications to the official estimation methodology.

The primary modification is that occupation employment and wage data at the establishment-level are imputed from a single donor. The imputation process involves two stages, a matching stage where potential donors are identified and a selection stage where the best donor is selected. The process is hierarchical, where the conditions for finding acceptable matches are sequentially relaxed. At the most detailed level of the hierarchy, a donor and frame unit will match on industry (6-digit NAICS), ownership (private or type of

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<sup>7</sup>Wages for the OEWS survey represent straight-time, gross pay, exclusive of premium pay. Base rate, cost-of-living allowances, guaranteed pay, hazardous-duty pay, incentive pay including commissions and production bonuses, tips, and on-call pay are included while back pay, jury duty pay, overtime pay, severance pay, shift differentials, non-production bonuses, employer cost for supplementary benefits, and tuition reimbursements are excluded from the reported wage.

<sup>8</sup>From 1999 to 2013, the SOC structure has expanded from 770 occupations to its current 821 occupations.

<sup>9</sup>These adjustments are not controls for industry and location. Rather, they are designed to convert the wages of the donor observations so that they more-closely approximate the recipient establishment's actual wages.

government), state, and county and will have similar employment levels. As the process continues through the hierarchy, geography is relaxed first and then ownership. It is not until very late in the process, after most of the frame units have already found an acceptable donor, that industry and employment proximity are relaxed. The matching stage often results in multiple potential donors. To preserve dispersion, the selection of a particular donor from the set of acceptable matches is random. Second, the OEWS sample is composed of certainty units, which are generally sampled every three years, and non-certainty units. Official estimates are based on data from the current panel and the previous five panels (because the OEWS is typically released in May, the five panels extend back to the November panel three years earlier). For purposes of integrating with other data, we center the sample on the reference year instead of using data from the five panels prior to May of the reference year, as do the published statistics. For example, under this approach, the sample for May 2017 is constructed using data from the following panels: May 2018, November 2017, May 2017, November 2016, May 2016, and November 2015. This results in a nationally representative sample centered on May 2017.

### 3 Empirical Analysis

After merging establishment occupation composition information into the BRS, we use the occupation composition of each BRS establishment to predict reported full-time and partial telework in a regression framework:

$$\omega_{ijt} = \sum_k \beta_{kjt} \theta_{ik} \quad (1)$$

where  $\omega_{ijt}$  is the proportion of employees in establishment  $i$  in telework status  $j$  at time  $t$ . Telework status can either be full-time or partial telework, and the time period is either pre-pandemic or during pandemic.  $\theta_{ik}$  is the proportion of employees in establishment  $i$  in occupation  $k$ . This regression is estimated imposing a restriction of non-negative coefficients on the least squares coefficients, so that  $0 \leq \beta_{kjt} \leq 1$ . The coefficients can be interpreted as a 1% higher proportion of employees in an establishment in occupation  $k$  will have a  $\beta_{kjt}\%$  higher proportion of employees in telework status  $j$  and pandemic period  $t$ .

The BRS asks respondents whether teleworking had increased for some or all employees since the start of the pandemic and whether increases in telework were expected to continue after the pandemic. In addition, the BRS asks what percent of employees currently telework all the time, some of the time but not all, and rarely or never. In order to get pre-pandemic estimates, we restrict the sample to only the 66% of BRS respondents reporting that they had not increased telework during the pandemic. The during-pandemic estimates are estimated on the full sample.

If the decision to increase telework is dependent on already having some amount of telework in the establishment pre-pandemic, then the sample chosen for the pre-pandemic estimates may be underestimated as the sample will be restricted to low telework establishments. However, if the telework take-up by occupation is similar regardless of the decision to increase telework during the pandemic, then the pre-pandemic take-up estimates remain unbiased. Assuming that employees who telework some of the time telework 50% of the time, our estimation shows that 5.5% of hours worked were done via telework pre-pandemic, which is virtually the same as the estimate in Barrero, Bloom, and Davis (2021). Our estimate for the portion of work hours worked at home as of summer 2021 is 14.7%.

In order to get the take-up rate for a particular occupation  $k$  and time  $t$ ,  $\rho_{kt}$ :

$$\rho_{kt} = \hat{\beta}_{k,full-time,t} + .5\hat{\beta}_{k,partial,t} \quad (2)$$

The full-time estimates are given a weight of 1 to imply that all work is done at home, and the partial telework estimates are given a weight of .5 to imply that half of work is done at home and half in the location of the establishment.<sup>10</sup> As a verification check, we compare these take-up estimates to the binary teleworkable classification by occupation done by Dey et al. (2021). For 5-digit SOC classifications where all of the detailed occupations within that category are determined to be teleworkable, the employment-weighted pre-pandemic take-up rate is 15.4% and the employment-weighted Summer 2021 take-up rate is 31.3%. For 5-digit SOC classifications where all of the detailed occupations are categorized as not teleworkable, there is a 1.7% pre-pandemic take-up rate (weighted by employment), and a 4.7% Summer 2021 take-up rate (weighted by employment). This is strong evidence of the signal contained in these estimates.

### 3.1 Telework by place of residence

In order to estimate foot traffic, we need information on where workers live as well as where they work. The QCEW provides detailed geographic information about the location of establishments but does not provide information about where the people who work for a given establishment live. We use published estimates by 2-digit SOC and Census tract from the 2015-2019 ACS<sup>11</sup> as the baseline for the number of employees residing in a Census tract in a particular 2-digit SOC occupation and working in a specified location. We then use the 2018 QCEW to estimate the number of jobs in each 2-digit SOC code within each Census tract. We reweight the ACS data so that the total number of 2-digit SOC employees working in an MSA is the same in both the ACS and the QCEW. The increase in local foot traffic in area  $g$  resulting from the fact that some individuals are now working at home can be calculated as

$$\tau_{residence,g} = \sum_k (\hat{\rho}_{k,during} - \hat{\rho}_{k,pre}) \times emp_{residence,k,g} \times \lambda_{k,m} \quad (3)$$

where  $emp_{residence,k,g}$  is the number of workers in the ACS in occupation  $k$  residing in geography  $g$ .  $\hat{\rho}_{k,during}$  and  $\hat{\rho}_{k,pre}$  are employment-weighted averages of  $\beta_{k,j,t}$  across 5-digit occupations within the 2-digit SOC codes, so that they can be applied directly to the published ACS data.  $\lambda_{k,m}$  is the reweighting factor for occupation  $k$  and geography  $g$  in MSA  $m$ , such that

$$\lambda_{k,m} = \frac{\sum_{g \in m} emp_{work,k,g}}{\sum_{g \in m} emp_{residence,k,g}} \quad (4)$$

where  $emp_{work,k,g}$  is the estimated number of jobs in geography  $g$  and occupation  $k$  based on the location of the place of work in the QCEW. This is summed over all geographies  $g$  in MSA  $m$ . The change in the number of workers going into the office for geography  $g$  is simply

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<sup>10</sup>All estimates for  $\beta_{k,j,t}$  are available at [https://www.michaeldaltoneconomics.com/files/ddl23\\_soc5.csv](https://www.michaeldaltoneconomics.com/files/ddl23_soc5.csv)

<sup>11</sup>Census Bureau (2020), American Community Survey (2015-2019), Table S2401.

$$\hat{\tau}_{work,g} = -1 \times \sum_k (\hat{\rho}_{k,during} - \hat{\rho}_{k,pre}) \times emp_{work,k,g} \quad (5)$$

Finally, we obtain a measure of the change in foot traffic by adding the two components  $\tau_{residence,g}$  and  $\tau_{work,g}$ .<sup>12</sup> Dividing by the adult population, the change in foot traffic in relative to the adult population in geography  $g$  is given by

$$\text{foot traffic change}_g = \frac{\tau_{residence,g} + \hat{\tau}_{work,g}}{\text{adult pop}_g} \quad (6)$$

Table 1 summarizes the foot traffic measure across Census tracts classified by urban classification and groups defined by an employment density measure. The employment density measure is simply the number of jobs divided by adult residential population of the Census tract. Each group represents a different point in the distribution within the urban classification, where Group 1 is below the median value, Group 2 is above the median but below the 75th percentile, Group 3 is between the 75th and 90th percentiles, Group 4 is between the 90th and 95th percentiles, and Group 5 is above the 95th percentile. The biggest decreases in foot traffic occurred in Census tracts where there is a high density of jobs per adult residents. For example, for the Census tracts in the top 5 percentile of large central metros, there are 56 jobs per adult resident and a foot traffic decline equivalent to about 7.4 full-time employees per adult resident in the Census tract. In contrast, census tracts with less dense employment tend to have small increases in foot traffic. This pattern exists across urban classifications. However, urbanization is relevant as more urbanized Census tracts have larger declines in foot traffic.

The percent of foot traffic change for each Census tract is presented in the online appendix.<sup>13</sup><sup>14</sup> In addition to the national map, maps for the DC, NYC, and San Francisco metropolitan areas are also shown in the online appendix. As can be seen from the zoomed-in maps, there are a handful of Census tracts, typically the most employment dense Census tracts, that have a very large decrease in foot traffic. Census tracts towards the outskirts of the center of the metropolitan area – typically considered “suburban” – have small increases in foot traffic.

### 3.2 Heterogeneous effects of foot traffic change on employment

We now examine how a reduction in local foot traffic affects employment in various sectors. Since some industries, like restaurants, are more reliant on in-person activities and nearby traffic for business, we may expect the employment in these sectors to be more impacted by changes in foot traffic.<sup>15</sup> We estimate the effect of foot traffic loss in geographical area  $g$  on employment in sector  $j$  by means of the following equation:

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<sup>12</sup>Our measure does not account for migration. As noted in the introduction, others have found evidence that reduced commuting has led to some population movement out of large metro areas. However, the effect of migration is small relative to the effect that is captured by our foot traffic measure. Regression results presented below are unaltered by including measures of migration net flow.

<sup>13</sup>[https://www.michaeldaltoneconomics.com/files/ddl23\\_onlineappendix.pdf](https://www.michaeldaltoneconomics.com/files/ddl23_onlineappendix.pdf)

<sup>14</sup>All estimates for  $\beta_{kjt}$  are available at [https://www.michaeldaltoneconomics.com/files/ddl23\\_foottraffic.csv](https://www.michaeldaltoneconomics.com/files/ddl23_foottraffic.csv)

<sup>15</sup>Similar questions have been addressed in the local jobs multiplier literature. Moretti (2010) estimates that a ten percent increase in tradable jobs employment ultimately leads to 3.3% increase in employment in local goods and services.

Table 1: Summary of Foot Traffic Change

Urban Classification	Jobs per Resident Group	Avg. Jobs per Resident	Avg. Foot Traffic Change (% of Population)	% of Businesses Downsizing or Relocating	Number of Census Tracts
Large Central Metro	1	0.43	1.05	7.34	5571
	2	1.9	-13.67	9.6	2787
	3	5.73	-57.11	10.12	1668
	4	14.05	-176.96	11.57	557
	5	56.17	-740.67	13.78	562
Large Fringe Metro	1	0.27	2.47	5.66	5455
	2	0.91	-2.85	6.62	2729
	3	1.98	-13.7	7.25	1637
	4	3.77	-32.88	6.94	537
	5	10.35	-115.72	9.25	557
Medium Metro	1	0.28	1.7	5.43	6588
	2	0.94	-3.21	6.22	3297
	3	2.15	-14.98	6.73	1958
	4	4.65	-45.1	7.87	678
	5	15.71	-149.61	7.57	659
Small Metro	1	0.26	1.66	5.38	3678
	2	0.79	-2.06	4.05	1835
	3	1.6	-9.31	4.87	1106
	4	2.72	-19.7	6.61	366
	5	5.79	-49.52	7.63	371
Micropolitan	1	0.25	1.2	3.78	3640
	2	0.62	-1.27	5.34	1814
	3	1.02	-3.88	5.03	1093
	4	1.46	-7.06	10.03	368
	5	2.48	-16.36	3.7	366
Noncore	1	0.2	1.16	2.92	2543
	2	0.44	-0.26	3.52	1273
	3	0.66	-1.62	3.42	764
	4	0.91	-3.51	5.86	247
	5	1.41	-5.99	4.4	262

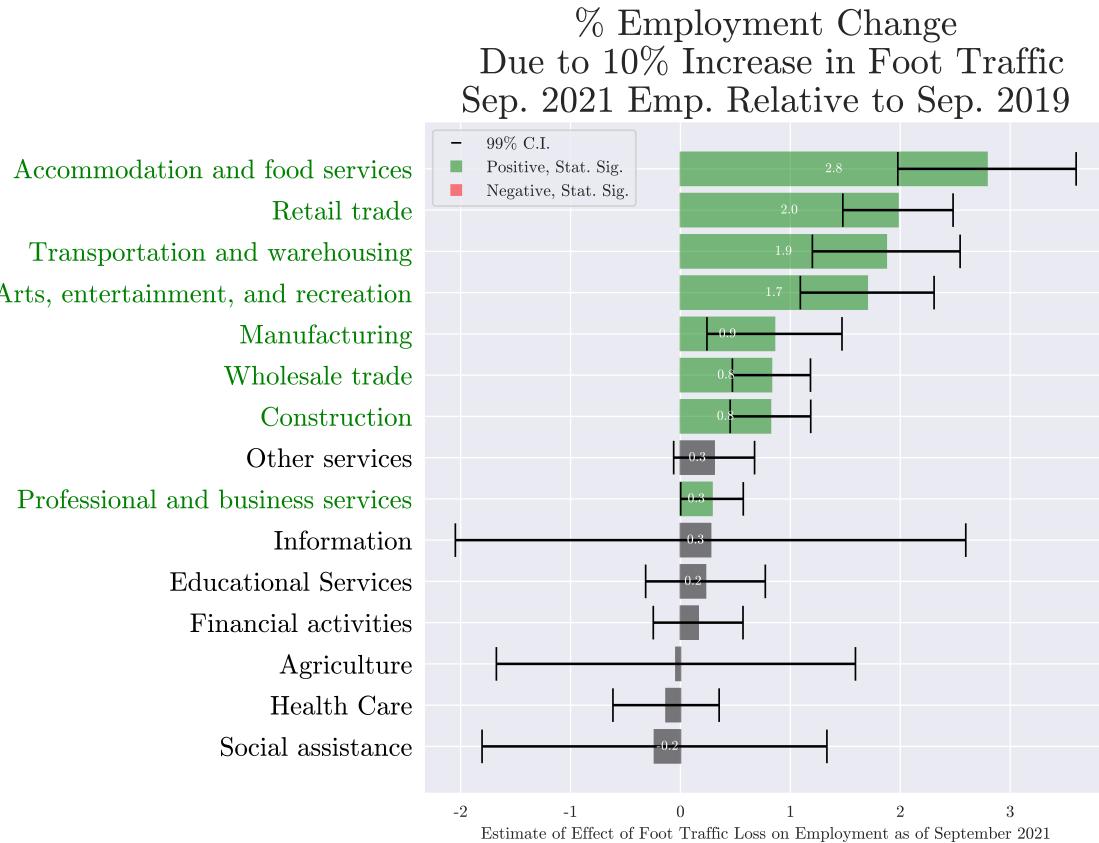
*Notes:* Group 1 includes all Census tracts below the median within the urban classification of the jobs per resident measure. Group 2 is between the median and 75th percentile. Group 3 is between the 75th and 90th percentile. Group 4 is between the 90th and 95th percentile. Group 5 is above the 95th percentile. Resident count is the adult population based on the 2020 American Community Survey. Number of jobs is based on a tabulation from the 2019 QCEW. Foot traffic change measure is as described in the paper. Census tracts with fewer than 100 adults are removed from this table.

$$\Delta emp_{jg} = \sum_j [\alpha_j \text{foot traffic change}_g + \lambda_j I_j] + X_{jg}\theta + \epsilon_{jg} \quad (7)$$

where  $\Delta emp_{jg}$  is the percent change in employment as of September 2021, relative to average monthly employment in  $j$  and geography  $g$  in 2019,  $X_g$  is a matrix of control variables that consist of county fixed effects and  $\lambda_j I_j$  are sector-specific fixed effects. The coefficients of interest are the set of  $\alpha_j$  which indicate how a change in foot traffic affects the employment of industry  $j$ .

The  $\alpha_j$  estimates from this regression are depicted in Figure 1. The unit of observation is a sector-Census tract, weighted by employment, and all standard errors are clustered at the county-level. The interpretation of the  $\alpha_j$  for accommodation and food services is that a 10% decrease in foot traffic in a Census tract leads to a 2.8% decline in employment for accommodation and food services in that Census tract, and this coefficient is statistically significant. Coefficients for retail trade, transportation and warehousing, and arts and recreation are also statistically significant at the 99% confidence level and with a magnitude greater than 1. The positive coefficients indicate that decreased (increased) foot traffic negatively (positively) affects employment in these sectors. Accommodation and food services and retail trade have the two largest coefficients and are likely heavily reliant upon in-person interactions for sales activity, which provides an intuitive explanation for the connection between a decline in foot traffic and a loss of employment in these sectors. The results remain comparable when using alternative sets of controls, such as net migration flow during the pandemic and interacting these migration flows by sector.

Figure 1



*Notes:* Regression coefficient estimates described in Equation 7. Each observation is a Census tract - sector. Standard errors are clustered at the county level. For the regression, the foot traffic measures are winsorized at magnitudes of 100%. Each Census tract-sector is weighted by its employment in 2019.

One way to check the validity of the results would be to estimate an equation with the same explanatory

variables but replacing the dependent variable with employment change from 2017 to 2019. Since the change in foot traffic is intended to measure the impact of the pandemic, there should be limited effect on prior period employment. Figure A.1 shows the resulting estimates – the only sector with a statistically significant coefficient is wholesale trade. Accommodation and food services and retail trade are not statistically significant and have small coefficients compared to their values in Figure 1. This provides evidence that the foot traffic measure is capturing real changes in behavior due to the pandemic.

### 3.3 The impact of relocation and foot traffic change on prevailing local rental prices

We conclude the analysis by estimating the effect of a reduction in foot traffic and firm relocation on local rental prices. We begin by estimating the relationship between increased teleworking and firm downsizing and relocation decisions.

Note that we can calculate the teleworking take-up rate for every establishment in the 2018 QCEW by :

$$\phi_{it} = \sum_k \hat{\rho}_{kt} \text{emp}_{ik} \quad (8)$$

BRS respondents are asked whether their establishment relocated, downsized or upsized their physical footprint since the start of the pandemic. We run separate probit regressions predicting the decision to downsize, upsize, or relocate, controlling for the pre-pandemic telework take-up rate at the establishment, the sector of the establishment, the urban classification of the county that the establishment is in, the population of the county in 2019 (using bins), the poverty rate of the county (using bins), state fixed effects, the size of the establishment in 2019 (using bins), and a dummy variable for whether the establishment is predicted to be renting its property.<sup>16</sup> Each establishment is equally weighted in the regression.

The only information used about the establishment as predictors in this regression is information that is known about the establishment prior to the pandemic. No other responses to the BRS survey are used in predicting the decision to change the physical footprint. This allows us to use the resulting estimates to predict the relocation decision for all establishments in the QCEW as it is not dependent on a response to the BRS. This yields a probability of downsizing (or upsizing or relocation) for each establishment in the 2018 QCEW.

The estimates for the renter dummy and for percent teleworking before the pandemic are shown in Table 2. Percent teleworking has a positive and statistically significant effect on relocating and downsizing and a null effect on upsizing. This is consistent with teleworking encouraging employers to change their physical footprint in response to fewer employees coming into the office. Additionally, the imputed information about whether an establishment is a renter also has a positive and statistically significant impact on relocation, downsizing, and on upsizing, suggesting renting makes the establishment more flexible with their physical footprint.

Having estimated the probability that every establishment in the universe downsizes, we aggregate across establishments within the same Census tract in order to estimate the proportion of Census tract employment that downsized. When summing, we weight an establishment's predicted likelihood of downsizing by its employment. Dividing the resulting sum by total employment for that Census tract yields an estimate of

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<sup>16</sup>An establishment is determined to be a renter if other establishments share the same physical address or the establishment has changed physical address within the last 10 years.

Table 2: Predicting Relocation

Regressor	Stat	Percent of Establishments		
		Relocating	Downsizing	Upsizing
Y/N: Renter	Coefficient	0.238	0.194	0.068
	(SE)	(0.026)	(0.026)	(0.024)
	[p-value]	[< .001]	[< .001]	[0.004]
Pct Teleworking Pre-Pandemic	Coefficient	0.006	0.006	0.002
	(SE)	(0.001)	(0.001)	(0.001)
	[p-value]	[< .001]	[< .001]	[0.063]

*Notes:* Results from regressions using the 2021 Business Response Survey. Additional controls include fixed effects for sector, urban/rural, population bins, poverty rate bins, state, size class.

the proportion of Census tract employment accounted for by establishments that downsize. Similarly, we estimate the proportion of Census tract employment accounted for by establishments that relocate or upsize. The map of downsizing is shown in Figure 2, with zoomed-in Figures in the online appendix for specific metro areas. Higher rates of downsizing can be observed in the employment-densest Census tracts, similar to areas with the highest rate of decline in foot traffic. Table 1 corroborates this by displaying the estimated percentage of businesses downsizing or relocating as of Summer 2021. Employment-dense Census tracts have higher rates of downsizing and relocating, though urban classification explains more of the variation for this than it does average foot traffic change.

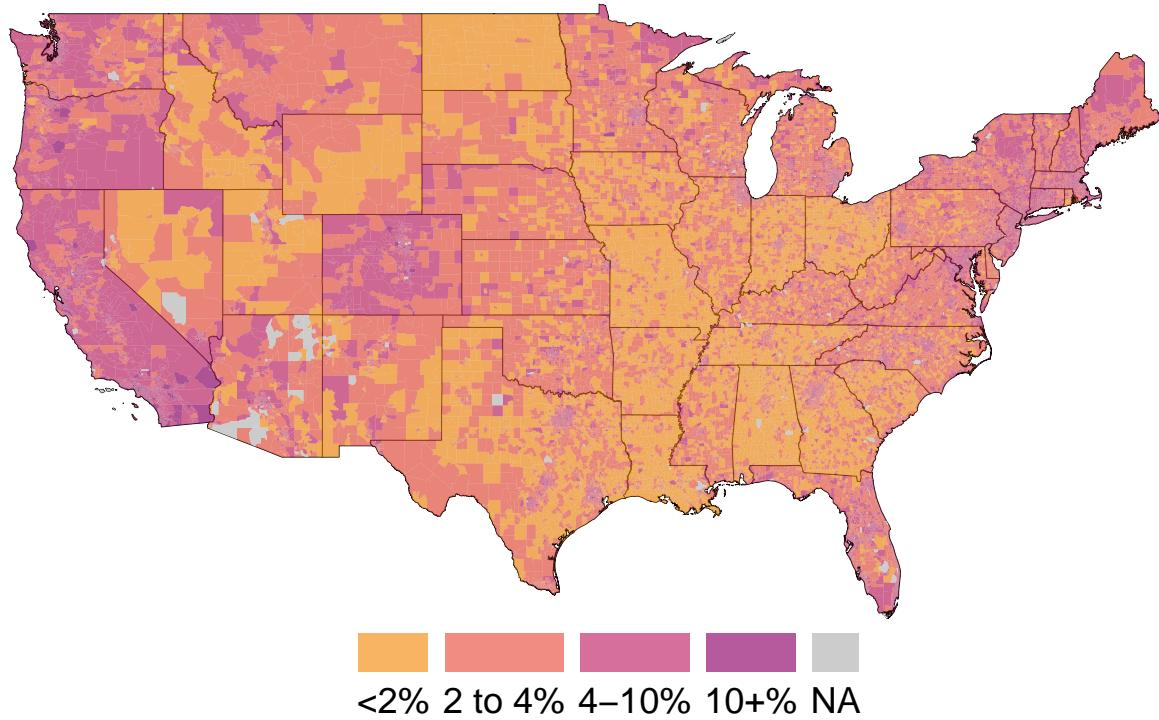
Lastly, we estimate the change in prevailing rental and housing prices from June 2019 to June 2021 for each Census tract using an OLS regression. Since Zillow only publishes rental and house price information at the zip code level, we match zip code-level information to each Census tract. The control variables in the equation are our zip code measures of the estimated proportions of employment subject to downsizing, upsizing, and relocation; our estimate of the change in Census tract foot traffic since the start of the pandemic; the log of Census tract population; the log of total wages in the Census tract; the change in rental prices from the prior two-year period; and Census tract-level poverty rates. Also included are county fixed effects, so that Census tracts are being compared to one another within a county. The rental regressions are restricted to zip codes with higher populations because Zillow rental information is only available for these zip codes.

The regression results are presented in Table 3. The unit of observation is a Census tract and standard errors are clustered at the county level. The results in the first and third columns are for the change in residential prices from 2019 to 2021, and the second and fourth columns are for 2017 to 2019. Presumably, decisions made during the pandemic – reflected in the foot traffic, downsizing, upsizing, and relocation estimates – should have no impact on rental prices during a period that does not include the pandemic. However, the downsizing estimate still shows as statistically significant even in the prior period estimates.

The estimates in the first column indicate that an increase in the proportion of establishments that downsize is associated with a statistically significant reduction in local rental prices. This coefficient can be interpreted as a 1% increase in establishments downsizing leading to a .2% decline in rental prices. A reduction in foot traffic is also associated with a fall in local rental prices – a 10% reduction in foot traffic

Figure 2

### Estimated Proportion of Establishments Downsizing by Census Tract



*Notes:* Map based on using estimates from the regression described in Table 2 and predicting for every establishment in the 2019 QCEW.

is associated with a 2.4% fall in rental prices.

The results in Table 3 also indicate that downsizing and a reduction in foot traffic are associated with statistically significant negative reductions in home prices from 2019 to 2021. Although the downsizing coefficients do not pass the placebo test, the foot traffic measure attenuates towards zero and is not statistically significant in either of the placebo regressions. The results remain comparable when using alternative sets of controls, such as net migration flow during the pandemic.

Table 3: Change in Prevailing Residential Prices in Zip Code

Regressor	Stat	Percent Change in...			
		Rent	2019 to 2021	2017 to 2019	Home Prices
		2019 to 2021	2017 to 2019	2019 to 2021	2017 to 2019
Proportion Estab. Downsizing	Coefficient	-21.26	-5.95	-33.53	-34.68
	(SE)	(4.72)	(1.91)	(3.65)	(3.66)
	[p-value]	[< .001]	[< .001]	[< .001]	[< .001]
Proportion Estab. Upsizing	Coefficient	-16.01	1.33	-5.32	-0.21
	(SE)	(4.53)	(2.9)	(2.9)	(2.95)
	[p-value]	[< .001]	[0.65]	[0.07]	[0.94]
Proportion Estab. Relocating	Coefficient	6.22	0.19	10.75	4.92
	(SE)	(3.11)	(2.45)	(3.1)	(4.12)
	[p-value]	[0.05]	[0.94]	[< .001]	[0.23]
Change in Foot Traffic	Coefficient	1.99	0.41	2.52	0.73
	(SE)	(0.45)	(0.29)	(0.34)	(0.38)
	[p-value]	[< .001]	[0.16]	[< .001]	[0.05]

*Notes:* Results from regressions where each observation is a Census tract matched to zip code-level rent and home price changes in Zillow. Additional control variables include county fixed effects, log of average wage in the Census tract and the change in residential prices in the prior 2-year period. Standard errors are clustered at the county level. For the regression, the foot traffic measures are winsorized at magnitudes of 100%.

## 4 Conclusion

Work from home has triggered a major change in where workers perform jobs. Teleworking rates have fallen from their height at the start of the pandemic, but are nevertheless well above their level before the pandemic. High telework rates in jobs that are well suited for working at home will undoubtedly remain, as workers realize the advantages they offer – especially reduced commuter time – and as employers learn that they can cater to these preferences at little or no cost. A reduction in the number of workers that commute has important effects on local economies. We have used several unique datasets to calculate and better understand these effects.

Combining the BRS, OEWS, and QCEW, we estimate telework take-up rates for nearly all occupations and establishments both before the start of the pandemic and during the summer of 2021. We also estimate the likelihood that establishments downsized or relocated. The telework estimates line up well with a binary classification based on O\*NET. For 5-digit SOC classifications where all detailed occupations within that category are determined to be teleworkable, the employment-weighted pre-pandemic take-up rate is 11.9% and the employment-weighted Summer 2021 take-up rate is 31.3%. For 5-digit SOC classifications where all detailed occupations are categorized as not teleworkable, there is a 2.3% employment-weighted pre-pandemic take-up rate, and a 4.7% Summer 2021 employment-weighted take-up rate.

Adding the Census data to the analysis allows us to estimate the change in foot traffic from before the pandemic to the summer of 2021 by Census tract. Our results indicate that the Census tracts with the greatest employment density had a very large decrease in foot traffic while tracts towards the outskirts of the center of the metropolitan area generally had small increases in foot traffic.

Our estimates also indicate that the increase in remote work had significant effects on local employment in non-tradable sectors. Specifically, a 10% decrease in foot traffic in a Census tract led to a 2.8% decline in employment for accommodation and food services and a 2 percent decline in retail trade employment.

Finally, we estimate the effect of reduced foot traffic and establishment downsizing and relocating on local real estate prices using zip code-level information from Zillow. The estimates indicate that reduced foot traffic had a significant negative effect on local rents and home prices.

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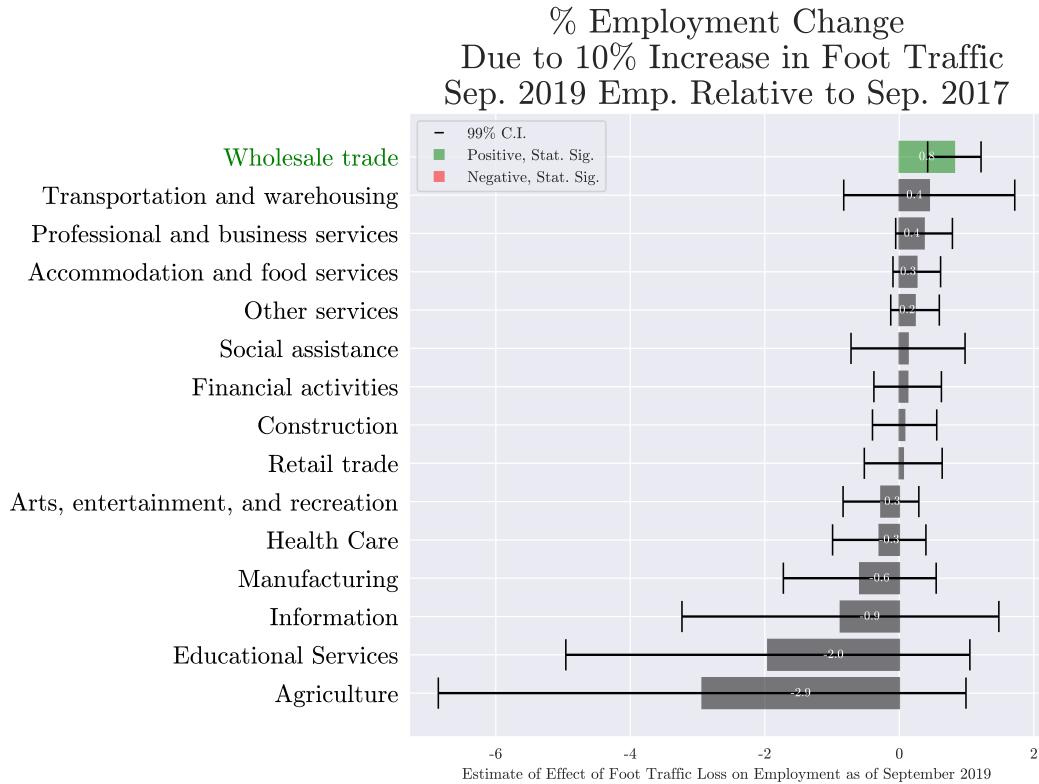
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## A Appendix

Figure A.1



*Notes:* Regression coefficient estimates described in Equation 7. Each observation is a Census tract - sector. Standard errors are clustered at the county level. For the regression, the foot traffic measures are winsorized at magnitudes of 100%.