Work from Home, Eat near Home?: The Reshaping Geography of Local Service Firms

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Abstract

The increase in the number of people working from home (WFH) not only has a direct effect on high WFH-potential industries, but also has more widespread impacts on the structure of cities and non-remote industries. In this paper, we investigate the effect of WFH on local service industries using Swedish administrative data and a difference-in-differences approach. We find evidence that restaurant production shifted towards more residential areas due to the increase in WFH and that this shift has persisted into the post-pandemic period, suggesting that there may be some longer-term spatial reorganization of cities. Restaurant workers are also impacted by these changes with workers employed at restaurants in more residential areas having increased earnings, likely driven by increased hours worked. We find no effects on employment or commuting distance suggesting no residential sorting by restaurant workers.

1 Introduction

The COVID-19 pandemic drastically changed many facets of life, not least of which was its massive impact on people's mobility patterns. While some of these effects were transitory, recent evidence suggests that effects appear lasting, at least in terms of an increased intensity of work from home (WFH) in many countries. While such a transition to increased WFH has been documented to have substantial direct effects on the workers and firms that actually make the transition (see e.g. Bloom et al. (2014); Angelici & Profeta (2023); Barrero et al. (2023)), there is still very little evidence on potential spillover effects on other parts of the economy. In this paper, we focus on changes in the spatial economic geography of cities and the impact this may have on *non-remote* industries and occupations. We provide novel evidence on these two economic effects by zooming in on restaurants and other local service firms. We draw on very detailed Swedish data to present the first evidence (to the best of our knowledge) on how changes in the spatial economic geography within cities in the post-COVID era affects the outcomes of firms and workers in local service industries.

By their very nature, most local service firms, such as restaurants, barbers, hair salons, and gyms, are unable to let their own employees work from home as the services they provide tend to require in-person interactions with customers. However, this does not mean that they are unaffected by the aggregate shift towards more remote and hybrid work. By definition, their customer base will spend more time in residential areas and less time in office districts if they do more of their work from home. If the demand for local services move in tandem with where the customers spend their time, then this will have a direct impact on the geographic distribution of demand for local services. Depending on where the local service firms are located, this may be good or bad news as expected demand changes would depend on how near they are to the working and resident areas of the individuals that now WFH. By extension, local service workers may see a changing geographic distribution of the demand for their services. We thus expect higher sales – and more work hours – in service production units that are located in the residential areas as compared to those located in office areas. For the service workers, this may affect their earnings in a positive or negative direction, depending on where they work. As workers adjust, it can either lead to longer or shorter commutes depending on the degree of occupational segregation on the housing markets, i.e. if service workers live closer to offices, or if they live closer to the remote workers' residences.

We begin by taking an establishment-level perspective to study the changing spatial allocation of local service sales. Our empirical application relies on Swedish micro data and, in the current version, we focus primarily on restaurants [to be extended to other industries]. From aggregate data we know that the restaurant sector, as well as the sectors of the other local service firms, have recovered well *as a whole* after the pandemic (Figure 1), but this recovery may mask changes in the geographic distribution. If there is a shift in restaurant sales due to increased WFH, we expect restaurants in more residential areas to thrive, while restaurants in office-dense areas may struggle to reach their pre-pandemic levels.

Figure 1: Aggregate restaurant sales (2016-2022)

Notes: This figure plots monthly, aggregated restaurant sales for all of Sweden from January 2016 through December 2022 based on the tax data for firms designated with restaurant industry code. Restaurant sales are separated into three categories: "total" sales, which is the sum of sales for all three tax categorizations (low, medium, and high); "food" sales, which is the sales for the medium tax category, of which food is the primary component for restaurants; and "alcohol" sales, which is the sales for the high tax category, of which alcohol is the primary component for restaurants. These sales numbers are not seasonally adjusted and are measured in thousands of SEK (Swedish krona).

To study these processes, we use highly detailed firm-level data on VAT payments, matched employer-employee data, and geographic location data on place of residence and place of work for all Swedish residents. Our data cover the period of January 2015 to December 2022 [to be updated]. We also use detailed geographic data on the COVID-19 intensity. Our main analysis compares restaurants in residential neighborhoods with restaurants in work-intensive neighborhoods before, during, and after (the intense phase of) the pandemic. Our hypothesis is that restaurants in residential neighborhoods benefit from the increase in WFH as compared to restaurants in work neighborhoods.

In line with this hypothesis, our results show evidence of a significant shift of restaurant production (proxied by restaurant sales) away from more working areas towards more residential neighborhoods during the COVID period, which extends into the early post-COVID period. This suggests that the shift to WFH in the wake of the pandemic has caused persistent effects on the geographic distribution of restaurant production. A set of auxiliary analyses corroborates this interpretation. Most importantly, restaurant sales are increasing more in residential neighborhoods with a higher-than-average share of residents that *can* work from home (as predicted from external data). This is true both during and after the COVID period, even conditional on having similar share of residents and workers. The data also allow us to separate between a pure "persistence" channel, which should be larger in areas (and restaurants) that needed to make larger adjustments during the pandemic (where local infections were more prevalent), and a more general "shift-of-norms" channel that would be independent of the local severity of the pandemic crisis. We find no evidence of differential changes in restaurant production based on exposure to COVID-19 adjustments, suggesting that the effects are driven by a general trend increase in work from home.

The geographic shifts in restaurant production provide evidence of a shift in the spatial organization of cities related to residential sorting. In the final part of our paper, we analyze if this has consequences for the local service workers. Indeed, we show that restaurant workers in residential areas experience earnings gains relative to similar workers in office areas, both during and after the COVID period. Given the institutional setting with relatively minor wage dispersion, we interpret these earnings effects as reflecting an increase in working hours. The effects are larger in areas where the residents are able to work from home. We find additional effects on employment during, but not after, the COVID period. Our final set of results study the commuting distances of restaurant workers. We find no differential effects of commuting between restaurants in residential vs. work-intensive areas. Overall, the results thus suggest that the WFH-transition had a significant impact on where restaurant workers earn their living, without affecting the average travel distance of these workers.

Our paper contributes to several streams of literature, most notably the literature looking at spatial and labor market effects of the pandemic and WFH. There are a few other papers looking into geographic consumption changes in restaurants, retail, and other similar firms and most of them find results that are inline with our results. However, these studies are limited to looking at the most intense period of the COVID-19 pandemic and are restricted to proxying firm sales with consumer-side credit card transactions (Alipour et al. (2022); Andersen et al. (2022); Carvalho et al. (2021)) or to a subset of establishments with firm-side data (Alexander & Karger (2023); Chetty et al. (2020)). The most similar paper to ours, and the only other paper we have seen exploring post-COVID effects of retail firms and restaurants, Duguid et al. (2023), find similar results as they document a shift in restaurants and retail towards residential areas. However, like some of the other previous studies, they rely on a subset of consumer credit card transactions to proxy for firm sales and focus only only a select group of US cities. In contrast, we are able to measure sales directly for the entire population of firms, giving us a cleaner estimate for the spatial reorganization of firm production. In addition to these spatial results, this is also the first paper (to the best of our knowledge) that empirically investigate the labor market effects of this spatial reorganization for local service industries, which we can directly measure at the worker level due to the granularity of the data.

This paper is structured as follows: Section 2 presents the context of WFH generally and in Sweden specifically as well as related previous literature. Section 3 discusses the key variables and data sources we use as well as provides descriptive statistics. Section 4 provides a road map for our estimation and identification strategies. Section 5 discusses the results of our main analysis as well as the potential mechanisms driving that result. Section 6 concludes.

2 Context

2.1 Work from home and the COVID-19 pandemic

Work from home is the term used to describe the employment situation where a worker performs at least some of her occupational tasks away from her physical workplace.[1] While this work system existed prior to the pandemic, it was not common and this type of work was concentrated amongst workers in certain industries and occupations (see Mas & Pallais 2020 for a survey of pre-pandemic work-from-home literature). That changed with the COVID-19 pandemic, as firms that had never previously considered WFH were forced to shift many workers to remote-working conditions. While the WFH experiment that COVID created was not successful for all occupations, it did reduce stigma related to WFH, reveal that many workers want to WFH more often, and show that productivity reductions related to WFH were less severe than firms expected (Aksoy et al. 2022; Barrero et al. 2023; Gill & Skans 2024). These factors suggest that WFH levels will remain higher in the post-pandemic period than in the pre-pandemic period. Barrero et al. (2021), for example, argue that WFH will persist beyond the pandemic, estimating that post-pandemic levels of WFH in the U.S. will be four times higher than pre-pandemic levels. Sweden is no exception to this trend as documented by Aksoy et al. (2022) who use global survey data which shows that Sweden generally mimics the trends on WFH perceptions and preferences of the other countries in the sample. Early post-COVID data supports this with data from the European Labor Force Surveys (accessed through Eurostat) indicating the number of employed persons working from home at least some of the time in 2022 (44.8%) was higher than in 2019 (37.2%) in Sweden. While work from home remains relatively high in the post-pandemic period, it is important to note that the ability to WFH is not uniform across industries and occupations as certain tasks cannot be done from home. This creates a wedge between who is able and who is unable to WFH.

2.2 Spatial allocation of cities

The COVID-19 pandemic and the increase in WFH is expected to have large effects on the spatial organization of cities and the geographic distribution of consumption. Researchers theorize that individuals that can work from home are expected to move away from expensive city center areas and shift

[1] This type of work structure (with geographic flexibility) is sometimes referred to as *work from anywhere* in the literature (e.g. Choudhury et al. (2021)).

towards cheaper outlying areas or even to cheaper cities or more rural areas (see e.g. Brueckner et al. (2023); Delventhal et al. (2022)). Initial empirical evidence supports this as researchers have found evidence in the US (Gupta et al. (2021)) and the UK (De Fraja, Matheson, Mizen, Rockey, Taneja & Thwaites (2021)) of shifting real estate prices caused by the increase in WFH due to COVID. This effect, however, seems to be concentrated mostly in large cities, with smaller cities having little (Delventhal et al. (2022)) to no (Ramani & Bloom (2021)) reallocation.

As workers move, firms are expected to reorganize as well. One theory, put forth by Ramani & Bloom (2021), posits that firms will move away from the dense city centers and closer to the periphery where rents are cheaper and where their workers live (especially if they are hybrid workers). This would create an empty city center, thus creating a "donut effect." Delventhal et al. (2022) propose an alternative theory based on a general equilibrium model of Los Angeles. They suggest that firms will concentrate even more densely into city center areas to take advantage of agglomeration effects while reducing office space to save costs as workers come in less often.

This spatial reorganizing by firms and residents should have a direct impact on the geographic organization of local service firms since these firms need to be near their customers as they require in-person transactions. If workers are now spending less time in the central business districts and more time near their residences, which are further away, local service firms will need to relocate to meet the changing spatial distribution of demand. In the short-run, this is expected to lead to short- to medium-run supply-demand mismatches (De Fraja, Matheson & Rockey (2021)) due to frictions in firm entry and exit, which should (eventually) lead to geographic reallocation of small service firms (De Fraja, Matheson, Mizen, Rockey, Taneja & Thwaites (2021)). Preliminary evidence of these short-term consumption changes can be found in the literature about the effect of COVID-19 on consumption patterns. Researchers have consistently found negative effects from the pandemic on offline consumer spending overall with large initial spending decreases, especially amongst firms in the restaurant and services industries (Akerman et al. 2022).[2] However, this overall decrease in spending was not uniformly distributed within cities, as firms in the city centers (Alipour et al. 2022; Domenech 2022) and in areas where the local infection rates were high (Akerman et al. 2022) suffered more. Some firms may have even benefited from the pandemic as firms in areas with "high WFH potential" (neighborhoods with a larger percentage of workers that could have worked from home prior to the pandemic but did not do so) saw no decline or even a slight increase in consumption (Alipour et al. 2022). After the pandemic, consumption overall and in restaurants and other service industries in particular have seen a good recovery after restrictions were relaxed or removed (Andersen et al. 2022; Carvalho et al. 2021).

[2] For evidence from other countries, see e.g. Denmark (Andersen et al. 2022), Germany (Alipour et al. 2022), Spain (Carvalho et al. 2021), China (Chen et al. 2021), and the U.S. (Alexander & Karger 2023; Chetty et al. 2020; Cox et al. 2020).

However, there is little research on if service establishments in different parts of the cities recovered differently or how they continue to be affected by long-term changes, like increases in WFH, that arose due to the pandemic. One paper (Duguid et al. (2023)) does look at post-COVID effects on retail establishments and document a shift in restaurants and retail towards residential areas, but they rely on a subset of consumer-side data (through credit card transaction) and limit the study to a subset of U.S. cities. There are two other papers that use firm-side transaction and revenue data, Alexander & Karger (2023) and Chetty et al. (2020), however they can only focus on a subset of U.S. firms (those that use "Womply" service where they get their data) and their data is only during the COVID pandemic period and thus are not able to make claims about the persistent effects beyond the pandemic. In contrast to these papers, we can look at the entirety of establishments in Sweden and can directly use firm sales data to measure these changes.

These shifts in residential and corporate locations are also expected to have some wider impacts on other non-remote industries. Althoff et al. (2020) predict that large work-from-home "shocks" will have stronger effects on larger cities than smaller cities both due to the larger geographic area and the higher concentration of skilled worker. These shocks, which will see the residential movement discussed above, is then expected to put undue burden on the low-skill, low-income workers who will bear the brunt of the economic fallout of such a shock. This would be primarily driven by shrinking local demand for the industries they work in, including the local services industries.

Our paper contributes to the literature by helping to fill some of these gaps and providing some empirical evaluations of these theorized effects. Specifically, this paper contributes in three main ways. First, this is one of the first papers providing empirical evidence of the persistent, post-COVID effects on the structure of cities and, in particular, to look at how this persistent increase in WFH shifts the geographic production of local service firms. To the best of our knowledge, this paper is also the first to investigate these changes in production directly using firm-side sales for the entire population of local service firms. Finally, this paper is, to the best of our knowledge, the first to look at spillover effects of WFH and the spatial reorganization of local service firms on the labor-market outcomes for non-remote industries, specifically for the local service workers. We further complement these results by digging into the mechanisms that drive these effects on local service firms and workers.

2.3 The Swedish context

In order to fully contextualize our results, it is important to understand the Swedish setting. Below we outline the context, focusing on work from home practices, COVID-19 policy, workplace eating habits, and city structure.

2.3.1 Work from home

Sweden had higher levels of WFH prior to the pandemic than many other countries, which was primarily due to a favorable industry composition, high levels of digital infrastructure, and favorable institutional and government policies (Gill & Skans (2024)). Yet, even with the high pre-pandemic levels, workers have still reported higher levels of WFH in the post-pandemic period both in the number of workers with some WFH and the amount of WFH being performed. This may be due to Sweden having a high capacity for work from home compared to other countries, with Dingel & Neiman (2020) estimating that about 44.2% of Swedish occupations can be done fully remotely, the third highest of the countries in their sample. Alternative estimates provide similar WFH levels for Sweden (see for example Adams-Prassl et al. (2022), Hensvik et al. (2020), or Mongey et al. (2021)). Despite these differences, the shift in the amount of WFH seems comparable with many other developed countries as the change in the percentage of workers with at least some WFH between 2019 and 2022 in Sweden is about the same as the change in the EU average (7.6pp/8pp increase for Sweden/EU average - European Labor Force Surveys, accessed through Eurostat).

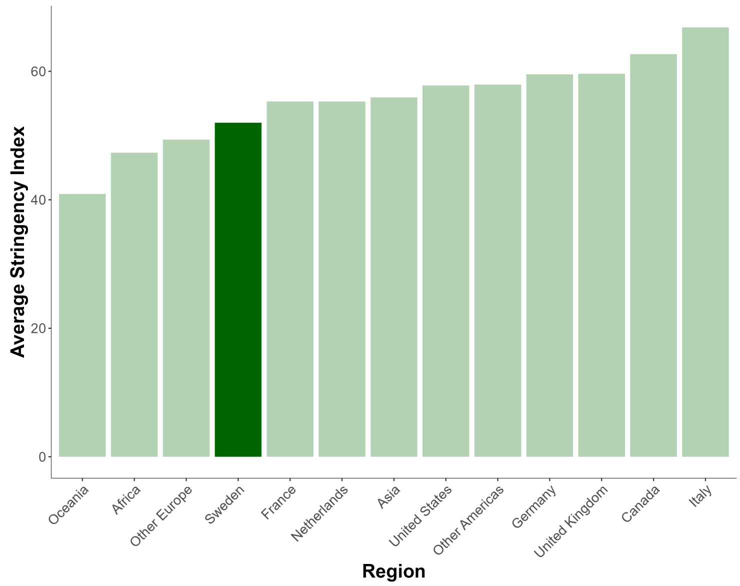
2.3.2 COVID-19 policies and responses

The Swedish context differs slightly from other countries in regards to their COVID-19 policy. Unlike most other European countries, Sweden never instituted a mandatory lockdown, instead relying on compliance with government recommendations. In addition, Sweden had a relatively lax approach during the first wave (approximately March through June 2020) with somewhat stricter policies during the second wave (approximately November 2020 through February 2021). Across the entire COVID period, Sweden policies were considered to be less stringent than most other developed countries (Figure 2), which seems to be driven by their low levels of formal requirements (Figure C.1).

In terms of COVID-19 policies directly affecting restaurants, the Swedish government never required restaurants and bars to close, but they did implement early closing hours, restrictions on alcohol sales, and capacity limits during stretches of the pandemic. All relevant COVID-19 restrictions were removed by September 29, 2021 (a brief outline of the relevant COVID-19 policies in Sweden can be found in Appendix A.1).

Despite these differences in COVID-19 policy, many pandemic outcomes remained similar because Swedish residents tended to follow the recommendations fairly well. Even without strict COVID policies, most businesses implemented WFH policies when possible, schools were closed, and transportation use was limited, which led to reduced mobility amongst the population. During the pandemic, daytime population in residential areas increased significantly, daytime population in industrial and commercial areas decreased significantly, and distance moved from homes during the day decreased significantly

Figure 2: COVID-19 Stringency Index



Notes: The COVID-19 Stringency Index is an index created by the Oxford Coronavirus Government Response Tracker (OxCGRT) project to measure the extent of government responses to COVID-19. The nine metrics used to calculate the Stringency Index are: school closures; workplace closures; cancellation of public events; restrictions on public gatherings; closures of public transport; stay-at-home requirements; public information campaigns; restrictions on internal movements; and international travel controls. A higher number indicates stricter COVID-19 policies. We look at the stringency index over the period which runs from January 1, 2020 through September 30, 2021. Sweden is colored in dark green for easy identification.
Source: Hale et al. (2021); processed by Our World in Data

in 2020 compared to 2019 levels (Dahlberg et al. 2020). This is similar to the mobility patterns of countries with stricter COVID-19 policies. When looking at COVID-related health outcomes, we can also see similarities between Sweden and other developed countries. Sweden suffered similar levels of both the number of cases and the number of deaths per 100,000 residents when compared to other developed countries such as the Nordic countries, western European countries, and the U.S. (Figure C.2). Considering the COVID policies and outcomes as well as the changes in WFH levels pre- and post-COVID, there is no reason to believe that the differing Swedish policy would affect the generalizability of the results.

2.3.3 Working and eating

A key presumption for our analysis is that changes in work patterns will alter the demand for restaurant services. This builds on the notion that parts of the demand for restaurant services comes from work-related eating. A survey directed to workers in several European countries in 2015 found that 18% of Swedish work lunches were sourced from restaurants near the workplace (Corvo et al. 2020), which is well above the average of the other European countries in the survey (13%). An additional 11% of Swedes source their lunches from onsite restaurants and canteens, which, while below the average among surveyed countries (22%), is not an insignificant amount. These numbers suggest that slightly less than a third of all work-related meals are sourced directly from restaurants at or close to the the workplace, both in Sweden and in Europe in general.

2.3.4 Urban geography

One dimension where Sweden does differ from some other countries, especially the U.S. and the large western European economies, is with respect to the urban composition of the country. Although more urbanized than their Nordic neighbors, Sweden has relatively few cities, and the cities tend to be smaller (Gill & Skans (2024)). Sweden has about 10 million inhabitants and only one city (Stockholm) has a population greater than 1,000,000 residents. Only two more (Gothenburg and Malmo) have populations greater that 250,000.[3] Since previous research shows that large cities tend to be more affected by WFH changes, we may expect that Swedish adjustments will provide lower bounds if generalized to countries with larger cities. To give a sense of how sensitive our results are to this dimension, we run alternative specifications where we directly test if the effects are different in the larger Swedish cities.

3 Data and Descriptive Statistics

Our data consists of matched employer-employee register data for all individuals and firms in Sweden from Statistics Sweden's LISA data. We then combine these data with monthly firm tax data, geographic data on individuals and establishments, and data on COVID-19 intensity. All of these data are collected and managed by Statistics Sweden and we access them through the SWECOV database.

Our data span 2015-2022. We define three different time periods: the pre-COVID period (from 2016 through February, 2020), the COVID period (from March 2020 through September 2021), and the post-COVID period (from October 2021 through the end of 2022). We define September 2021 as the end of the COVID period since most COVID-19 recommendations and restrictions in Sweden regarding restaurants and mobility were removed by September 29, 2021, however, our results are robust to different definitions of the post-COVID period.

Our level of treatment (for all specifications) and our unit of analysis (for some specifications) is the "DeSO," a statistical area defined by Statistics Sweden that is similar to a neighborhood. The DeSO designation was created in 2018, but it has been applied retroactively. The DeSOs were constructed based on geographic areas with the same population, so all DeSOs in our data have roughly the same number of residents, but can vary in size of the area and in the number of individuals working in the area. There are 5,984 DeSOs, each classified into on of three categories. Category "A" DeSOs are in rural areas (18.0%), category "B" DeSOs are population-concentrated areas but outside of major

[3] These categorizations are based on the 2023 values in the World Population Review.

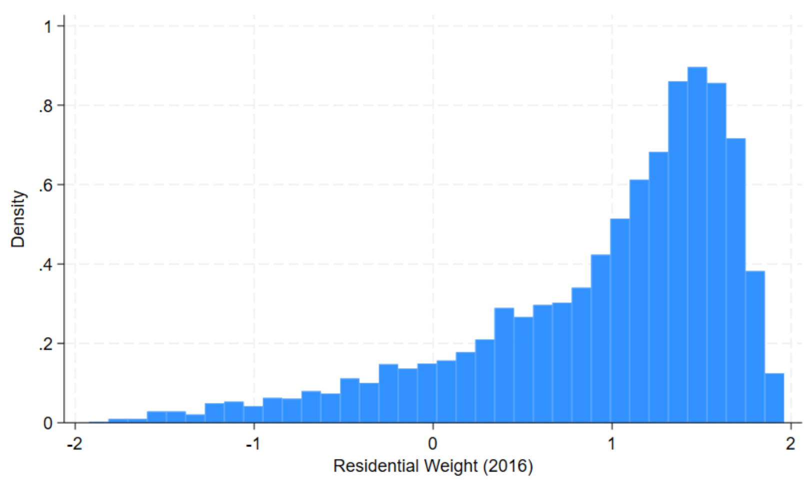
municipality areas (9.7%), and category "C" DeSOs are central locations within municipalities (72.3%). For our main analysis, we only use B- and C-type DeSOs (4,904 cases) due to the more dispersed nature and sizes of the category A areas, however our main results are robust to the inclusion of category "A" DeSOs.

Our treatment variable captures the "residential weight" of each neighborhood. For each DeSO, we calculated the difference between the number of residents living in the DeSO and the number of individuals whose workplace is located in the DeSO divided by the mean of these two scores:

$$Residential\ Weight_j = \frac{residents_j - workers_j}{\left(\frac{residents_j + workers_j}{2}\right)}$$

where j indexes the DeSO. A natural interpretation of the score is as a symmetric percent difference between the number of residents and the number of workers. A benefit of computing the score this way (dividing by the average of the two) is that we avoid extreme outliers both in DeSOs with a very low number of residents and in DeSOs with a very low number of workers. The residential weights are theoretically bounded to range from -2 in the least residential (only workers) case to $+2$ in the most residential (only residents) case.

Figure 3: Distribution of 2016 residential weights ("B" & "C" DeSOs)



Notes: This figure plots the distribution of residential weights in 2016 for all "B"- and "C"-category DeSOs in Sweden.

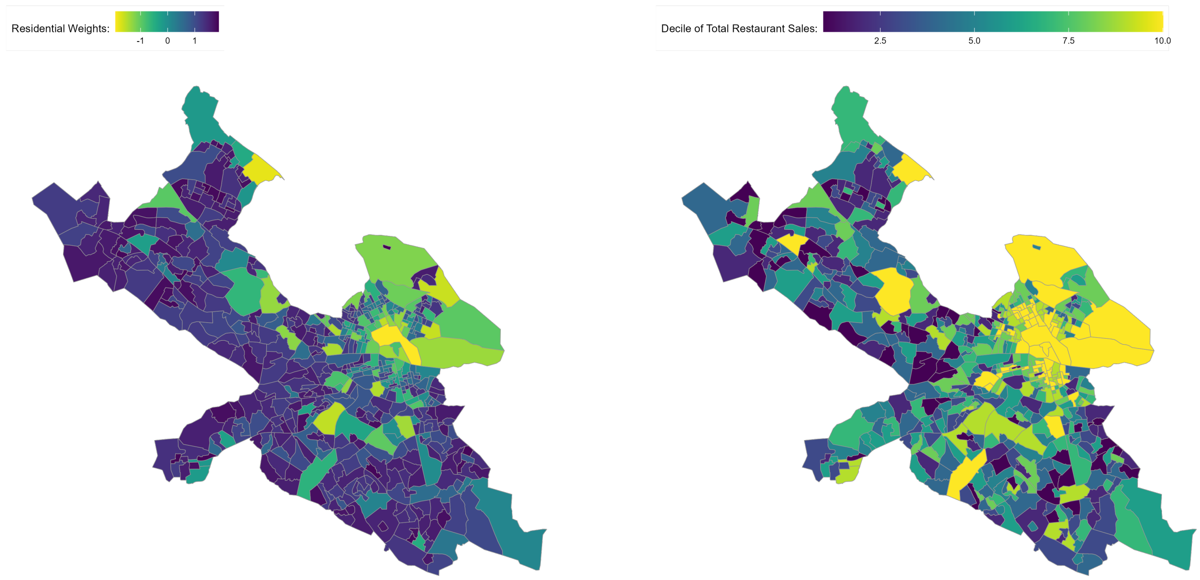
The distribution of the 2016 residential weights for the "B" and "C" DeSOs can be found in Figure 3. The distribution spans most of the possible range of residential weights, with a clear left skew. The average residential weight is just under 1 as shown in Table 1. In the Appendix we verify that the residential weights are stable over time (see Figure C.4). Panel (a) of Figure 4 presents a map of the Stockholm municipality DeSOs colored by their residential weight in 2019.

In our analysis, we study several outcome variables related to the spatial structure of local service

Figure 4: Stockholm Municipality DeSOs - 2019

(a) Residential weights

(b) Decile of restaurant sales



Notes: Both panels in this figure show the DeSOs for the Stockholm municipality. Panel (a) colors the DeSOs by 2019 residential weight with yellower (lighter) colors indicating more working neighborhoods and the bluer (darker) colors representing more residential neighborhoods. For context, the area in the center right (where there are more working DeSOs) is the primary central business district of Stockholm. Panel (b) presents the same map, but colors the DeSOs by decile of restaurant sales in 2019. Yellower (lighter) colored DeSOs are higher in terms of the decile of restaurant sales, while bluer (darker) DeSOs are lower in terms of the decile of sales. We use restaurant sales deciles instead of actual sales to remove skewing caused by outliers. To show that these relationships remain fairly consistent over time, we create the same figure using 2016 values for residential weights (panel (a)) and restaurant sales deciles (panel (b)) in Figure C.3.

industries. Our first main outcome variable is plant *sales*, which acts as a proxy for plant production. Sales are derived from the VAT data using the sum of sales across the three possible VAT rates (high, medium, and low).[4] The VAT data are recorded at the firm level and some firms have establishments (restaurants) in multiple locations. We allocate VAT to establishments using employment weights. We thus allocate firm sales to each specific restaurant in proportion to the share of the firm's employees that worked in each restaurant during the previous year. For new firms with multiple restaurants, we allocate the VAT equally across all establishments.[5] Finally, we aggregate these distributed sales to the DeSO-level. The distribution of residential shares and restaurant sale deciles at the DeSO level in Stockholm during 2019 is shown in Figure 4. In addition, we look at the effect on "food" sales and "alcohol" sales separately in order to investigate if different types of restaurants seem to be more affected. We use sales at the medium (high) VAT rate to proxy for "food" ("alcohol") sales as food (alcohol) is the main component of restaurant sales in this tax classification.

We also study outcomes for the restaurant workers focusing on earnings, employment and com-

[4]The exact conversion between VAT and sales is calculated as: $\textit{Total Sales} = \textit{VAT high} * 4 + \textit{VAT medium} * 8.3333 + \textit{VAT low} * 16.6667$, using numbers provided by the Swedish tax authority. Sales are measured in SEK (Swedish krona).

[5]For firms where some establishments have prior employment and others not, we use the associated assignment rule for each, and then normalize it by dividing them by the total assigned.

muting. For these outcomes, we have monthly data starting from 2019, when Statistics Sweden began collecting this data at the individual, monthly level. We use the firm-level industry to isolate the restaurant workers. We restrict workers to only be associated with one restaurant per month, using the highest earnings.[6]

We start by looking at employment, which we define by the number of workers in the restaurant industry in a DeSO in a time period. To construct this variable, we assign a binary variable that equals 1 if the worker works in the restaurant industry in that year and then aggregate to the DeSO level. As discussed above, workers are restricted to one establishment, and thus DeSO, per month, but the DeSO can change between months. At the worker level, we look at earnings and commuting. Earnings is reported at the monthly level.[7] To compute commuting distances, we calculate the centroid (geometric center) of the DeSO where the workers live and the DeSO where they work and convert. We then measure the angular distance between these centroids using the Haversine formula.[8] We use these "as the crow flies" distances as proxies for commuting time.

We utilize additional data to investigate the underlying mechanisms. We construct measures of WFH potential at the DeSO level for both residents and workers to see if effects are larger where the potential for WFH is greater. Our preferred measure relies on data from Wave 1 (July-August 2021) and Wave 2 (January-February 2022) of the Global Survey of Working Arrangements (Aksoy et al. (2022)). We use these data to estimate an out-of-sample logit regression, based on the data from France, Germany, and the Netherlands. We regress the binary variable of whether or not an individual works from home on demographic characteristics (age, gender, education, and family status) as well as industry dummies. Prediction accuracy for the Swedish respondents within the survey is approximately 67%.[9] We then assign the prediction weights to all individuals in our Swedish data. These weights are then aggregated up to the DeSO level. We use "predicted" WFH based on the pre-pandemic composition of neighborhoods in order to remove any selection bias caused by ex-post residential sorting.

To disentangle general shifts in demand from persistent effects of local adjustments due to the pandemic, we use data on local exposure to COVID-19. Our preferred measure is a count of DeSO-level deaths in 2020 and 2021 attributed to COVID-19. We separately compute deaths amongst residents and amongst workers in each DeSO and then convert them into deaths per 100 residents or workers, respectively. "Attributed COVID deaths" includes both deaths confirmed to be COVID-19 through

[6]Further criteria is imposed on the additional workers (details of this criteria can be found in Appendix Section A.2).

[7]We use "social security based earnings" as our basis, which is the earnings category that the vast majority of restaurant workers receive.

[8]Due to the short distances involved, the Haversine distance provides a good approximation, despite the simplifying assumption that the Earth is a sphere.

[9]Prediction weights estimated by the logit can be found in Table B.11. The education and industry variables are redefined from the survey definitions in order to match with our Swedish data.

tests as well as those believed to be COVID-19 but not formally tested. We check the robustness of our specification using only confirmed COVID-19 deaths per 100 residents as well as with measured based on confirmed COVID-19 cases per 100 residents, symptomatic COVID-19 cases per 100 residents, and COVID-related ICU admittance per 100 residents.

We begin by focusing on restaurants with the intention of expanding to other local service industries.

DeSO-level descriptive statistics from 2019 can be found in Table 1.[10] The first two columns represent the lowest (least residential) and highest (most residential) quartiles, respectively. The third column presents the descriptive statistics averaged across all of the DeSOs. The quartiles are similar in most demographic dimensions as well as in WFH predictions.

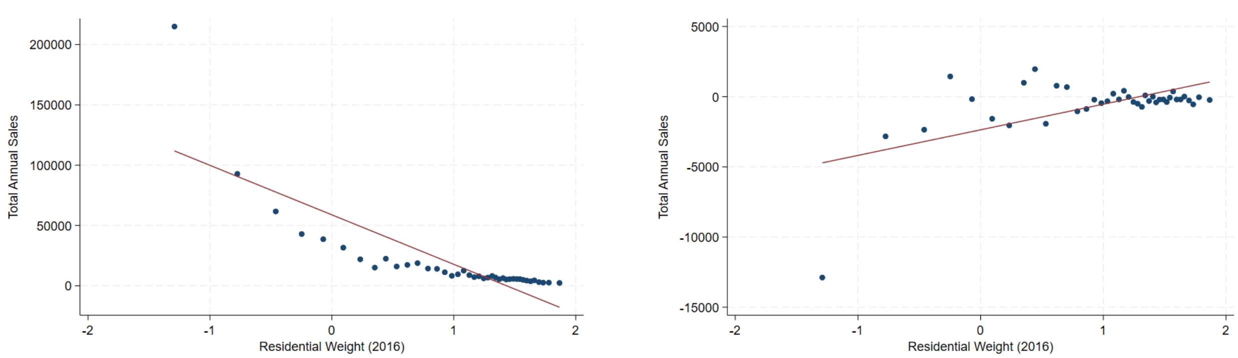
Residents in work intensive areas have somewhat higher average monthly income, possibly as a consequence of other amenities that attracted high income residents pre-COVID. The most-working intense neighborhood also have a higher share of COVID deaths among residents, but a lower share among workers.

A key difference from our perspective is that there are fewer restaurants, and fewer restaurant workers, in the most residential DeSOs. Restaurant workers in the residential areas also earn less but commute shorter distances (about 10 percent). In line with what is suggested by the table, restaurant sales are negatively correlated with the residential weight (panel (a) of Figure (5), Spearman's $= -0.47$, p-value < 0.001). Interestingly, however, there is a clear tendency towards a reversal of the correlation between 2019 and 2022; more residential neighborhoods have, on average, larger sales growth than more working neighborhoods during this period (panel (b) of Figure 5). Our empirical exercises will scrutinize this pattern further.

Figure 5: Correlations between 2016 residential weight and restaurant sales

(a) Total restaurant sales (2019)

(b) Difference in restaurant sales (2022-2019)



Notes: In these figures, we show the binned scatter plot of 2016 residential weight and the average monthly total restaurant sales per DeSO. Panel (a) shows the correlation with 2019 restaurant sales. Panel (b) shows the correlation with the difference in sales between 2022 and 2019. Total restaurant sales are measured in SEK. The red lines represent the estimated linear relationship. To show this relationship is not driven by outliers, we recreate the figure in panel (b), but with the extreme negative residential weight DeSOs removed (Figure C.5).

[10] Overall descriptive patterns, and the relationships between quartiles, remain similar across time before COVID, see Table A.1 for data describing 2016.

Table 1: Annual descriptive statistics - 2019
(B- and C-type DeSOs)

	Quartile 1 (most working)	Quartile 4 (most residential)	All
Average 2016 residential weights	-0.12	1.66	0.96
Share of "C" DeSOs	0.95	0.93	0.88
Average residents per DeSO	1,792	1,794	1,779
Average workers per DeSO	2,739	175	974
Average age	43	45	44
Average share female	0.48	0.51	0.51
Average share with a partner	0.85	0.86	0.85
Average share with children	0.38	0.36	0.37
Average share with at least tertiary education	0.35	0.34	0.34
Average number of passenger cars	665	637	677
Average monthly income (SEK)	3,232	2,078	2,611
Average restaurant plants per DeSO	8.36	1.52	3.74
Average share predicted to WFH (residents)	0.37	0.39	0.38
Average share predicted to WFH (workers)	0.36	0.36	0.35
Average COVID deaths amongst residents (per 100 residents)	0.172	0.120	0.153
Average COVID deaths amongst workers (per 100 workers)	0.020	0.050	0.034
Average employment for restaurant workers	56.16	4.33	20.23
Average earnings for restaurant workers (SEK)	15,670	9,550	12,467
Average commuting distance for restaurant workers (meters)	8,870	8,090	8,423
Average restaurant total sales per person	2.66	0.18	0.93
Average restaurant food sales per person	2.00	0.16	0.72
Average restaurant alcohol sales per person	0.63	0.03	0.20
N	1,226	1,226	4,904

Notes: These descriptive statistics are based on 2019 data and are averages across the DeSO-level statistics. These descriptive statistics include all establishments but only the DeSOs in the "B" and "C" categories (we removed rural neighborhoods). Quartile 1 and Quartile 4 are the lowest and highest quartiles by 2016 Residential Weight, with Quartile 1 being the least residential and Quartile 4 being the most residential.

4 Empirical Framework

In order to estimate the effects of an increase in WFH on the spatial organization of cities and the labor market for restaurant workers, we consider the COVID-19 pandemic as an exogenous treatment that caused an unanticipated jump in WFH. Since the pandemic caused many other types of adjustments, we focus our interest on changes that remained after the most intense COVID period. To identify the effects, we use our residential weights as a measure of how exposed to "treatment" each DeSO was during this period. Under plausible assumptions of monotonicity, neighborhoods with high residential weights should experience a growth of WFH, whereas areas with lower weights should have experienced a reduction in the number of present workers. The monotonicity assumption seems reasonable as neighborhoods with many more residents than workers (high residential weight) are likely to experience an increase in remote or hybrid workers with a relatively small effect on the number of workers entering the neighborhood. Similarly, areas with many more workers than residents (low residential weights) are likely to have fewer workers coming to the neighborhood but a small effect on the number of residents remaining at home. Since it is likely that the magnitudes of these responses vary with the composition of residents and workers (i.e. who, not just how many), we provide additional exercises based on our WFH predictions described in the data section.

Our strategy uses a generalized difference-in-differences specification where we compare the pre-COVID period to the post-COVID period (with estimates for the COVID period included for completeness), across neighborhoods with different residential weights. Because we are interested in both spatial effects and labor market effects, we rely on two different specifications, one at the neighborhood level, and one at the individual (restaurant worker) level.

4.1 Neighborhood-level specifications

Our main specification at the neighborhood level is conducted using the DeSO as our unit of analysis. Formally:

$$\begin{aligned} \mathit{Outcome}_{d,m,y} = \delta_0 &+ \beta_1 RW_d * \mathit{Post\text{-}period}_{m,y} + \beta_2 RW_d * \mathit{COVID\text{-}period}_{m,y} \\ &+ \delta_1 \mathit{Post\text{-}period}_{m,y} + \delta_2 \mathit{COVID\text{-}period}_{m,y} + \theta_{m,y} + \theta_d + \epsilon_{d,m,y} \end{aligned} \tag{1}$$

where d, m, and y index DeSO, month, and year, respectively. RW_d is the residential weight of the DeSO, fixed at the 2016 level. We include month-year fixed effects ($\theta_{m,y}$) and DeSO fixed effects (θ_d). Standard errors are clustered at the DeSO level.

We look at two different outcome variables at the neighborhood level: (i) plant production in terms of aggregated plant sales in logs and (ii) employment in the restaurant industry in terms of number of workers in both levels and logs. For both outcome variables, we are particularly interested in the hypothesis that β_1 is significantly different from zero. Thus our null and alternative hypotheses are $H_0: \beta_1 = 0$ and $H_A: \beta_1 \neq 0$, respectively. We also discuss the COVID period effects, but these are less well identified and are discussed in more exploratory terms and to add perspective to our interpretation of β_1.

This model provides us with estimates of the overall relationship between changes in outcomes across neighborhood as a function of their initial residentiality. To verify that the estimated effects are driven by WFH, as we hypothesize, we interact our main specification with the DeSO-level WFH potential described in the data section. The estimated model is a straightforward extension of equation 1, fully interacted with the WFH potential:

$$\begin{aligned} Outcome_{d,m,y} = {} & \delta_0 + \alpha_1 RW_d * \textit{Post-period}_{m,y} * \textit{WFH-pred}_d \\ & + \alpha_2 RW_d * \textit{COVID-period}_{m,y} * \textit{WFH-pred}_d + \beta_1 RW_d * \textit{Post-period}_{m,y} \\ & + \beta_2 RW_d * \textit{COVID-period}_{m,y} + \beta_3 \textit{WFH-pred}_d * \textit{Post-period}_{m,y} \\ & + \beta_4 \textit{WFH-pred}_d * \textit{COVID-period}_{m,y} + \delta_1 \textit{Post-period}_{m,y} \\ & + \delta_2 \textit{COVID-period}_{m,y} + \theta_{m,y} + \theta_d + \epsilon_{d,m,y} \end{aligned} \tag{2}$$

where $\textit{WFH-pred}_d$ is the DeSO-level WFH prediction either for residents or for workers. In the workers specification, we include the WFH prediction for both workers and residents to remove any colinearity effect since they are strongly related (Pearson's correlation = 0.73, p-value < 0.001). The other components are the same as in Specification 1. Standard errors are again clustered at the DeSO level.

In this specification, we are primarily interested in the effect on our triple interaction term for the post-period (α_1), which estimates the *differential* effect across periods on our outcome by WFH potential, holding the residential weight constant. Thus our null and alternative hypotheses here are again $H_0: \beta_1 = 0$ and $H_A: \beta_1 \neq 0$, respectively. A significant effect for this triple interaction would provide evidence in favor of our main hypothesis.

We estimate a similar interaction model to investigate the role of local severity during the COVID-period. Here, we use the measure of COVID-deaths among workers and residents described in the data section (as well as the alternative COVID exposure variables for robustness checks). We hypothesize that if our main effect is driven by long-term effects of the COVID experience, then we would expect neighborhoods that were more affected during the COVID era, in terms of having more residents or workers die from the virus, to have stronger relative effects during the post-COVID period. If, on the other hand, we do not find any differential effects across these areas, it seems more plausible that the main results are due to a general shift of norms and behavior towards working, and eating, from home. Formally, we estimate:

$$\begin{aligned} Outcome_{d,m,y} = {} & \delta_0 + \alpha_1 RW_d * \textit{Post-period}_{m,y} * \textit{COV-deaths}_d \\ & + \alpha_2 RW_d * \textit{COVID-period}_{m,y} * \textit{COV-deaths}_d + \beta_1 RW_d * \textit{Post-period}_{m,y} \\ & + \beta_2 RW_d * \textit{COVID-period}_{m,y} + \beta_3 \textit{COV-deaths}_d * \textit{Post-period}_{m,y} \\ & + \beta_4 \textit{COV-deaths}_d * \textit{COVID-period}_{m,y} + \delta_1 \textit{Post-period}_{m,y} \\ & + \delta_2 \textit{COVID-period}_{m,y} + \theta_{m,y} + \theta_d + \epsilon_{d,m,y} \end{aligned} \tag{3}$$

where $\textit{COV-deaths}_d$ is the DeSO-level percentage of the population with COVID-related deaths (either for residents or for workers). The other components are the same as in Specification 1. Standard errors are again clustered at the DeSO level.

As above, we focus on the triple interaction term (α_1). This term estimates how our main effect differs by COVID-19 exposure. Thus our null and alternative hypotheses are again $N_0: \beta_1 = 0$ and $N_A: \beta_1 \neq 0$, respectively.

4.2 Worker-level specifications

We also estimate effects on restaurant workers using a worker-level model where individual restaurant workers (by time) is the unit of observation. Our main worker-level specification is:

$$\begin{aligned} Outcome_{i,m,y} = \delta_0 &+ \beta_1 RW_d * Post\text{-}period_{m,y} + \beta_2 RW_d * COVID\text{-}period_{m,y} \\ &+ \delta_1 Post\text{-}period_{m,y} + \delta_2 COVID\text{-}period_{m,y} + \theta_{m,y} + \theta_d + \theta_i + \epsilon_{i,m,y} \end{aligned} \tag{4}$$

where i, m, and y index the individual restaurant worker, the month, and the year, respectively. RW_d is the 2016 residential weight of the DeSO where the individual works. We include month-year fixed effects ($\theta_{m,y}$), DeSO fixed effects (θ_d), and individual worker fixed effects (θ_i). Standard errors are clustered at the individual worker level.

For this specification, we use two different outcomes: (i) earnings, in both levels and in logs, and (ii) commuting distance of restaurant workers. Because the residential weights are based on the DeSO of where the individual works, our estimation for the worker-level regressions are conditional on being employed in that month.

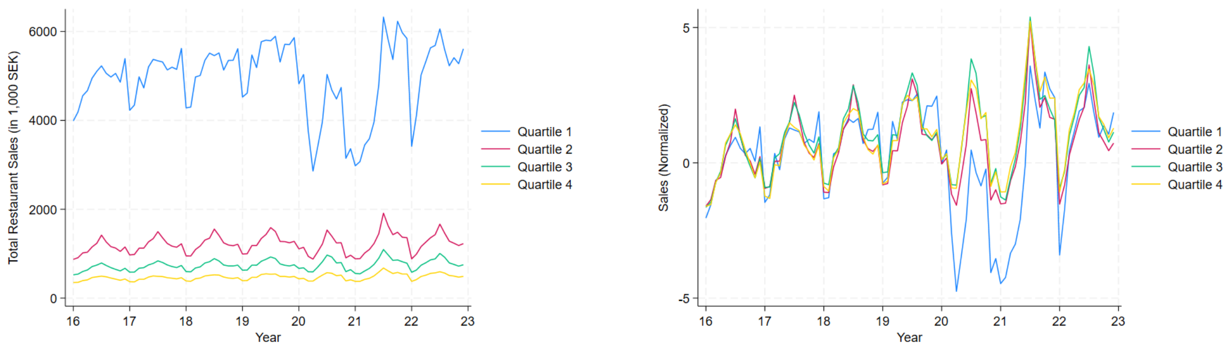
4.3 Identifying assumptions

In order for our estimates to be properly identified, we need to assume that changes in restaurant sales (and other outcomes) would have been unrelated to residential weights in the absence of the COVID induced surge in WFH. While this assumption is not directly testable, we assess the plausibility by inspecting trends in the pre-COVID period. Figure 6 shows the data on restaurant sales by residential weight quartile from 2016 onwards. Panel a) displays the raw data for completeness, but we focus our attention to panel b) where the data have been normalized by the 2016 average value within each quartile. As is evident, the pre-COVID trends are similar across the quartiles of residential weights. The fact that all four quartiles grew in tandem before the pandemic supports our assumption that they would have have continued to do so without the pandemic surge in WFH. We present a corresponding visual inspection for our labor market outcome variables – although this analysis is restricted to a much shorter time period starting in 2019 – and find a very similar pre-pattern for employment (Figure 7) and earnings (panel (a) of Figure 8). For commuting, the pre-trends are nosier, but there is no evidence of a systematic differential trend (panel (b) of Figure 8).

To more formally check the reasonableness of the parallel trends assumption, we run a Granger-type causality test where we include indicator variables for the pre-period years to get some indication if there could be a linear pre-trend. The exact specification is formalized as:

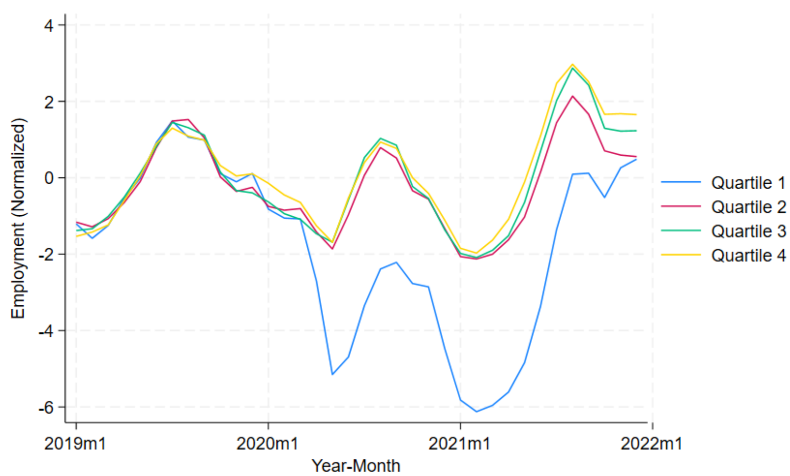
Figure 6: Restaurant sales by 2016 residential weight quartile

(a) Total sales (b) Sales normalized by 2016 average and SD



Notes: These figures plot the average monthly total restaurant sales for DeSOs by 2016 residential weight quartile from January 2016 through December 2022. Quartile 1 represents the DeSOs with the lowest residential weights (most working DeSOs) while Quartile 4 represents the DeSOs with the highest residential weights (most residential). Panel (a) plots the raw total restaurant sales (in thousands of SEK) to show the level difference between quartiles. Panel (b) plots the sames sales figures but normalized by the average sales and standard deviation for sales in 2016 for that quartile. They are normalized by subtracting the 2016 mean and dividing by the 2016 standard deviation.

Figure 7: Employment by 2016 residential weight quartile (normalized by 2019 average per quartile)



Notes: This figure plots the average monthly employment for restaurant establishments in a DeSO by 2016 residential weight quartile from January 2019 through December 2022. Quartile 1 represents the DeSOs with the lowest residential weights (most working DeSOs) while Quartile 4 represents the DeSOs with the highest residential weights (most residential). Employment is normalized by the average employment and standard deviation for sales in 2019 for that quartile. They are normalized by subtracting the 2019 mean and dividing by the 2019 standard deviation. Employment is normalized because of the large initial level differences between quartiles. vspace-1mm

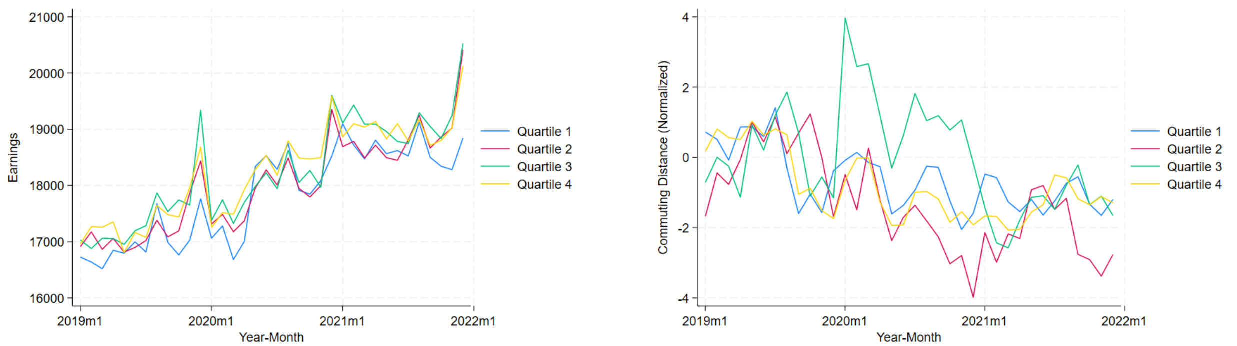
$$\log(Sales_{d,m,y}) = \delta_0 + \beta_1 RW_d * Post\text{-}period_{m,y} + \beta_2 RW_d * COVID\text{-}period_{m,y} + \boldsymbol{\gamma} \sum_{k=2017}^{2019} RW_d * Year\text{-}k_{m,y}$$
$$+ \delta_1 Post\text{-}period_{m,y} + \delta_2 COVID\text{-}period_{m,y} + \boldsymbol{\psi} \sum_{k=2017}^{2019} Year\text{-}k_{m,y} + \theta_{m,y} + \theta_d + \epsilon_{d,m,y}$$

where "Year-k" represents the indicator variable for the associated year and 2016 is used as the reference year. For this specification, we are interested in the values of the coefficients $\boldsymbol{\gamma}$ which estimate any potential linear trend in the pre-periods. The coefficients for the interaction terms are plotted in Figure 9 and the estimates of all the coefficients can be found in Table B.12.

Figure 8: Restaurant worker earnings and commuting distance by 2016 residential weight quartile

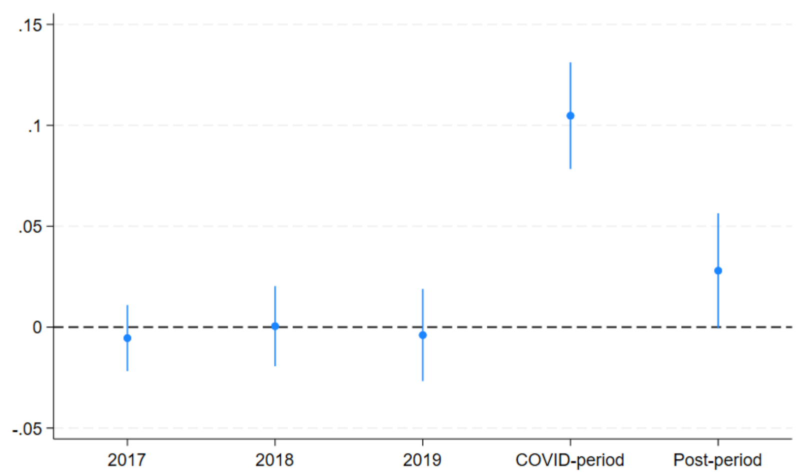
(a) Restaurant worker earnings

(b) Commuting distance normalized by 2019 average and SD



Notes: *Notes:*Panel (a) plots the average monthly earnings for restaurant workers in a DeSO. Because wages are relatively similar, raw earnings are plotted. Panel (b) plots the commuting distance normalized by average commuting and standard deviation for sales in 2019 for that quartile. They are normalized by subtracting the 2019 mean and dividing by the 2019 standard deviation. Commuting is normalized because of the large initial level differences between quartiles. Both panels separate DeSOs by 2016 residential weight quartile where Quartile 1 represents the DeSOs with the lowest residential weights (most working DeSOs) while Quartile 4 represents the DeSOs with the highest residential weights (most residential). They both plot data from January 2019 through December 2022.

Figure 9: Estimated coefficients for the interaction variables of the Granger-type causality test



Notes: This figure plot the coefficients of the test for linear pre-trends. Plotted here are only the coefficients for the interactions between the 2016 residential weights and the binary time variables from the specification in equation 4.3. For the full set of estimated coefficients, refer to Table B.12. 95% confidence intervals are shown and standard errors are clustered at the DeSO-level.

As expected, considering the patterns displayed in panel b) of Figure 6, there is no evidence of a significant per-period trend. In contrast, all interaction coefficients with pre-period years are estimated close to 0, suggesting no differential changes over the years based on residentiality. Furthermore, we find large coefficients for both the post-COVID period and the COVID period, which anticipate our main results.

Along with the parallel trends assumption, we also need to assume no anticipation effects. Because of the speed, severity, and uncertainty of the COVID-19 pandemic (especially in the early stages), we believe there is little opportunity for firms to adjust to COVID-19 responses before the onset of government policies in March 2020. There was only around 3 months of of prior discussion about COVID-19 and most of that included high levels of uncertainty about if/where it would spread and how governments would respond. Few restaurants would have anticipated such rapid and strict government responses and, even if they believed it might occur, the stickiness of commercial real estate and labor markets make it difficult and highly risky for firms to systematically attempt to respond to any anticipation. Furthermore, we see no evidence of a anticipation effect when looking at the pre-trends as sales for firms in all quartiles were similar to each other and similar to the previous years until March 2020 when government policies were imposed (panel (b) of Figure 6). We also run alternate specifications where we relax our definition of the COVID-period to all of 2020 and 2021 and find no discernible differences in the results (Table B.7).

5 Results

5.1 Spatial Reallocation

We first present the results of residentiality on DeSO-level restaurant sales for both the sample of all establishments in the DeSO and the sample of incumbent establishments in the DeSO, defined as establishments that exist within our data for at least every month from January 2019 through December 2021. In our analysis, we focus on the effects from the full sample of establishments, but present the effects from the incumbent sample as well. Along with total restaurant sales, we also present the results for food-related sales and alcohol-related sales separately. The results of our main specification are found in Table 2.

We find that there is a positive and significant effect of residential weights on restaurant sales in both the COVID-period and the post-period. This suggests that the more residential a neighborhood was pre-pandemic, the larger relative change in restaurant sales the neighborhood experienced. To get a better idea of what these estimates mean, we can extrapolate these effects across our full sample and compare the DeSO with the highest residential weight (1.98) to the DeSO with the lowest residential weight (-1.93). These results estimate that the most residential neighborhood had a relative increase of 11.3 percentage point in restaurant sales between the pre- and post-COVID periods compared to the most working neighborhood. Similarly, these same neighborhoods differed in sales by 41.4 percentage points in the COVID-period relative to the pre-period, on average. We find very similar results using only the incumbent establishments as well suggesting that the results are not driven by establishments entering or exiting the market during the pandemic.

Looking at the breakdown by type of sales, we find positive and significant effects on both food sales and alcohol sales in the post-COVID period (as well as the COVID period). Because we see

Table 2: Effect of residentiality on restaurant sales

	Full Sample (2016-2022)			Incumbent Establishments (2019-2022)		
	Total sales	Food sales	Alcohol sales	Total sales	Food sales	Alcohol sales
RW x Post-period	0.029**	0.034***	0.049***	0.024**	0.025***	0.053***
	(0.012)	(0.011)	(0.019)	(0.011)	(0.009)	(0.016)
RW x COVID-period	0.106***	0.100***	0.111***	0.110***	0.099***	0.158***
	(0.011)	(0.011)	(0.017)	(0.009)	(0.008)	(0.014)
DeSO-level F.E.	Y	Y	Y	Y	Y	Y
Month-year F.E.	Y	Y	Y	Y	Y	Y
R^2	0.08	0.07	0.01	0.08	0.09	0.02
N	321,489	315,880	238,927	173,428	170,020	127,645

Note:This table presents the results for our main specification using restaurant sales. In these specifications, we use three different measures of sales as outcome variables: total sales (columns 1 and 4), which are all sales that a restaurant has; food sales (columns 2 and 5), which are all the sales in the medium tax category; and alcohol sales (columns 3 and 6), which are all the sales in the high tax category. Columns 1-3 present the results for the full sample of firms and uses sales data from January 2016 through December 2022. Columns 4-6 present the results for a subset of incumbent establishments and uses sales data from January 2019 through December 2022. "Incumbent establishments" is the subset of restaurants that existed from the beginning of 2019 through the end of 2021. Restaurant sales is measured in logs for all three sales categories (total, food, and alcohol). "RW" is an abbreviation for the residential weights. Residential weights are fixed at the 2016 level. Standard errors are clustered at the DeSO-level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

large differential effects on alcohol, it is unlikely that only lunch restaurants, where alcohol sales are much lower, were affected, but this increase in WFH likely affected consumption patterns for dinner as well. One thing to note is there is a large loss of observations for our estimates for alcohol sales due to restaurants in those DeSOs not having positive alcohol sales. However, even restricted to DeSOs with positive alcohol sales, the large effect we see for alcohol sales suggests that our results hold even given the contemporaneous growth in the food delivery industry since alcohol cannot be purchased for delivery from restaurants.

One concern about these results is that they are not driven by the residentiality of neighborhoods, but by characteristics that might correlate with residentiality, most notably demographic or income characteristics. In order to alleviate these concerns, we run a series of regressions where we add interactions between a control variable and both the COVID period and post-COVID period at the DeSO level. We look at several demographic characteristics including the percent of residents over 65 years old (retired population), percent female, percent with a partner (married or cohabiting), percent with at least one child, percent with at least a tertiary education as well as the number of passenger cars in the DeSO and both median and average income. The results for total restaurant sales for the fill sample of firms can be found in Table 3.

Looking at the table, we get consistent results when we include these control variables and they are comparable with our main result. The coefficients for the post-COVID period range for 0.023 to 0.039 which is similar to our 0.029 coefficient we estimated in our main regression. Similarly, all of these estimates are statistically significant at the 5% level with the exception of the estimate for the

Table 3: Effect of residentiality on total restaurant sales including demographic interactions

	% over age 65	% female	% with partner	% with children	% with tertiary education	passenger cars	Median income	Average income
RW x Post-period	0.028**	0.031**	0.026**	0.023*	0.028**	0.039***	0.028**	0.030**
	(0.012)	(0.012)	(0.013)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
RW x COVID-period	0.113***	0.107***	0.100***	0.100***	0.102***	0.108***	0.107***	0.106***
	(0.011)	(0.011)	(0.011)	(0.012)	(0.011)	(0.011)	(0.011)	(0.011)
DeSO-level F.E.	Y	Y	Y	Y	Y	Y	Y	Y
Month-year F.E.	Y	Y	Y	Y	Y	Y	Y	Y
R^2	0.07	0.08	0.01	0.12	0.03	0.02	0.00	0.00
N	321,489	321,489	321,489	321,489	321,489	321,489	321,489	321,489

Note: In this table, we present the results of our main specification with the inclusion of demographic characteristics interacted with the post-COVID and COVID periods. All of the characteristics are from the previous year. The estimated coefficients for the residential weight interactions are presented in the table. This table presents to results for total restaurant sales measured in logs. "RW" is an abbreviation for the residential weights. Residential weights are fixed at the 2016 level. Standard errors are clustered at the DeSO-level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

specification with "percent with at least one child" control. Based on these results, it does not seem likely that our effects are being driven by demographic or income-related composition of the DeSOs.

5.1.1 Mechanisms

To investigate the underlying mechanisms, we focus on two main channels: (i) whether the effects are driven by changes in the amount of WFH or some alternative time trend and (ii) whether the effect is driven by lasting effects of COVID exposure, or by a general shift of norms or behavior.

We expect that this effect is predominately driven by the post-pandemic increase in WFH, however the previous specification does not explicitly rule out alternative channels that could have also been triggered by the pandemic (e.g. shift in personal restaurant preferences). To speak to this channel, we run the interacted specification, based on equation 2 where we exploit variation across neighborhoods in the WFH potential of residents and workers. If WFH is the main driver of the main results, then we should see stronger positive effects for neighborhoods with residents with higher WFH potential, and stronger negative effects for neighborhoods with workers with higher WFH potential. We run separate regressions with WFH predictions for the residents and for the workers (including resident prediction as a control) in the DeSO. The results are displayed in Table 4.

We find that there are significant, positive effects on neighborhoods with higher predicted WFH in the post-COVID period and duirng the COVID period. This suggests that restaurant sales for DeSOs where many residents can work from home was higher than restaurant sales for DeSOs with a similar level of residentiality, but a lower WFH potential. Looking at the post-COVID period for the full sample, we estimate a coefficient of 0.005 which indicates that restaurant sales in a DeSO with 10% more WFH residents saw a 5 percentage point larger increase, holding residential weights constant. For the COVID period, the corresponding estimate was 7 percentage points. As with the overall effect, we find comparable results when only including sales of incumbent establishments, suggesting that the effect was not driven by restaurant exits or entry.

If we look at the effect on the predicted WFH of those working in the DeSO, we find no effect

Table 4: Effect of WFH prediction and residentiality on total restaurant sales

	Residents		Workers	
	Full Sample (2016-2022)	Incumbent Establishments (2019-2022)	Full Sample (2016-2022)	Incumbent Establishments (2019-2022)
RW x Post-period x resident-WFH	0.005***	0.004***	0.005**	0.004**
	(0.002)	(0.001)	(0.002)	(0.002)
RW x Post-period x worker-WFH			-0.000	0.000
			(0.002)	(0.001)
RW x COVID-period x resident-WFH	0.007***	0.006***	0.001	0.001
	(0.001)	(0.001)	(0.002)	(0.002)
RW x COVID-period x worker-WFH			0.006***	0.006***
			(0.001)	(0.001)
DeSO-level F.E.	Y	Y	Y	Y
Month-year F.E.	Y	Y	Y	Y
R^2	0.05	0.06	0.05	0.05
N	321,489	173,428	321,489	173,428

Note: In this table, we present the results for total restaurant sales (in logs) for both the full sample of firms (from January 2016 to December 2022) and incumbent establishments (from January 2019 to December 2022). "Incumbent Establishments" is the subset of restaurants that existed from the beginning of 2019 through the end of 2021. "RW" is an abbreviation for the residential weights. "resident-WFH" is calculated as the mean of the WFH prediction probability for DeSO residents (all columns) and "worker-WFH" is the equivalent for workers (columns 3 & 4). They are both based on out-of-sample predictions using G-SWA survey responses for France, Germany, and the Netherlands. Residential weights are fixed at the 2016 level. Standard errors are clustered at the DeSO-level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

for the post-COVID period and the effect for predicted WFH of residents remains. However, for the COVID period, we see the opposite effect - the effect for predicted WFH for workers is positive and significant while the effect for residents disappears.

The second channel we explore is whether the overall effect is driven by COVID-19 exposure. Here, we run the specification based on equation 3 that interacts the main model with Covid-19 exposure. As before, we run separate regressions for residents in the DeSO and for workers in the DeSO for both the full sample and the sample of incumbent establishments. The results are shown in Table 5.

Table 5: Effect of COVID exposure and residentiality on total restaurant sales

	Residents		Workers	
	Full Sample (2016-2022)	Incumbent Establishments (2019-2022)	Full Sample (2016-2022)	Incumbent Establishments (2019-2022)
RW x Post-period x COVID-deaths	0.023	0.041	0.015	−0.084
	(0.073)	(0.069)	(0.209)	(0.163)
RW x COVID-period x COVID-deaths	0.089	0.151**	−0.138	−0.167
	(0.083)	(0.072)	(0.209)	(0.190)
DeSO-level F.E.	Y	Y	Y	Y
Month-year F.E.	Y	Y	Y	Y
R^2	0.08	0.08	0.08	0.08
N	321,489	173,428	321,489	173,428

Note: In this table, we present the results for total restaurant sales (in logs) for both the full sample of firms (from January 2016 to December 2022) and incumbent establishments (from January 2019 to December 2022). "Incumbent Establishments" is the subset of restaurants that existed from the beginning of 2019 through the end of 2021. "RW" is an abbreviation for the residential weights. "COVID-deaths" are calculated as the percentage of the DeSO population that died over the whole COVID period for residents (columns 1 & 2) and workers (columns 3 & 4) in the DeSO. Residential weights are fixed at the 2016 level. Standard errors are clustered at the DeSO-level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Here, we find no differential effects for DeSOs with the same residential weight, but different COVID-19 exposure for either the post-period or the COVID-period. This means that areas that were hit harder by COVID, and where COVID policies would be more evident and more adhered to, did not see increased or decreased relative restaurant sales. This would suggest that the direct effects of COVID policies are not a likely driving factor of the general effects found. These similar effects indicate that the pandemic many have acted as a trigger for a more uniform "shift of norms" channel. Considering that there is evidence that WFH is at least partially driving the effect, it seems likely that the pandemic increased the amount of WFH across DeSOs, which led to more residential neighborhoods being relatively positively affected and working neighborhoods being relatively negatively affected.

5.2 Labor Market Effects

Following our estimates for the spatial reallocation of local service firms, we investigate whether these shifts (and the more general WFH transition) has effects on mobility and labor market outcomes of restaurant workers. We begin by looking at employment (estimated at the neighborhood level) and then look at earnings and commuting (both estimated at the worker level).

5.2.1 Employment

We first look at changes in restaurant worker employment between the pre-COVID period and the COVID and post-COVID periods. We use both number of workers as well as log employment as outcome variables. The results are presented in Table 6.

Table 6: Effect of residentiality on restaurant employment (2019-2021)

	Number of workers	Log employment
RW x Post-period	0.862	0.023*
	(0.728)	(0.012)
RW x COVID-period	7.911***	0.065***
	(1.371)	(0.009)
DeSO-level F.E.	Y	Y
Month-year F.E.	Y	Y
R^2	0.07	0.08
N	176,544	129,785

Note: The data in this specification only spans from 2019-2021. Results for employment are presented both in terms of actual number of workers and as log number of workers. "RW" is an abbreviation for the residential weights. Residential weights are fixed at the 2016 level. Standard errors are clustered at the DeSO-level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

First, we find that there is a large relative change in employment during the COVID period. Assuming the average effect is true across the whole sample, total change in restaurant employment between the pre-COVID period and this period was approximately 31 workers more positive for the

DeSO with the highest residential weight compared to the DeSO with the lowest residential weight. However, this effect seems to be driven primarily by reduced employment in less residential neighborhoods and not by increased employment in more residential neighborhoods. This is because, as seen in Figure 7, restaurant employment in more residential neighborhoods remained fairly similar between the pre-COVID and COVID periods, but there were large drops in employment in the least residential neighborhoods. We do not find any significant differential effects on employment in the post-COVID period. This suggests that the differential effects on restaurant employment are confined to the COVID period and persistent effects from COVID-19 on restaurant employment is relatively uniform across DeSOs of different residentiality.

When we look into differential effects by predicted WFH, we find positive and significant effects for neighborhoods where the workers have higher predicted work from home in both the COVID period and post-COVID period (Table B.1). We see this same pattern when looking at employment levels and log employment. This effect could be driven by areas with a higher predicted number of workers with WFH being more harshly hit early in the pandemic, so they needed to do more hiring to return to pre-pandemic levels.

When we look at the specification including COVID exposure, we find no differential effect when looking at resident exposure which is similar to the previous results. We do estimate some effect when looking at worker exposure, but this seems concentrated in the COVID period and does not seem to be a persistent effect, especially when looking at the log employment specification which would remove the initial level differences across DeSOs.

5.2.2 Earnings

If restaurants in more residential areas have seen a relative increase in sales, but there are no differential post-COVID effects on on employment, then we might expect to see differences in the change in earnings to compensate. To explore this, we look at the earnings of workers in the restaurant industry as a whole as well as the earnings for tenured workers, defined as workers that remained at the same establishment for the entire period of 2019-2021. These results can be found in Table 7.

Looking at the entire sample of restaurant workers, we find positive and significant differential changes in earnings between the pre-COVID period and both the COVID period and post-COVID period. This suggests workers at restaurants in more residential neighborhoods saw a relative increase in earnings in both periods. If we compare the highest and lowest residential weight DeSOs using these estimates, it suggests that restaurant workers in the most residential neighborhood saw approximately a 525 SEK ($\sim$50 USD) relative increase in earnings per month compared to the least residential neighborhood in the post-COVID period. Comparing these same neighborhoods using the COVID-

Table 7: Effect of residentiality on restaurant workers' earnings (2019-2021)

	Full Sample		Tenured Workers	
	Levels (in SEK)	Logs	Levels (in SEK)	Logs
RW x Post-period	137.42***	0.004*	275.49***	0.015***
	(32.74)	(0.002)	(84.38)	(0.003)
RW x COVID-period	337.82***	0.031***	393.24***	0.018***
	(19.41)	(0.001)	(40.11)	(0.002)
Individual F.E.	Y	Y	Y	Y
Month-year F.E.	Y	Y	Y	Y
R^2	0.00	0.00	0.00	0.00
N	3,337,706	3,337,706	462,647	462,647

Note: In this table, we present results for earnings in both levels (column 1 and column 3) and logs (column 2 and column 4). We present the results for the full sample of workers (columns 1 and 2) and for tenured workers (columns 3 and 4). "Tenured workers" is the subset of workers that remained in the same establishment for all of 2019-2021. The data in this specification only spans from 2019-2021. 'RW" is an abbreviation for the residential weights. Residential weights are fixed at the 2016 level. Standard errors are clustered at the Individual-level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

period estimate suggests approximately a 1,320 SEK (∼126 USD) relative increase in earnings per month. If we look at the estimates for the tenured workers, we find even larger differences. Looking at log earnings, we lose significance for the post-period for the full sample, but the results are qualitatively similar and we still see very large and significant effects within the sample of tenured workers. This suggests our results are (to some extent) robust to functional form, particularly when we focus on the intensive margin with the tenured workers sample. Since worker wages in Sweden are relatively sticky, we expect that these earnings effects are mostly driven by changes in the number of hours worked. Workers in more residential areas are likely being asked to work more hours to compensate for the increase demand by consumers, especially since employment has remained fairly consistent.

Digging into the mechanisms driving these differential effects, we find similar patterns to our results for restaurant sales. First, we look into if WFH seems to be driving the earnings effects by using the predicted percentage of WFH in the DeSOs. These results can be found in Table B.3. We find significant and positive differential effects in both the COVID and post-COVID periods for workers employed at establishments in DeSOs with a higher percentage of residents predicted to WFH but with similar residential weights. To give context to the coefficients for the full sample (Column 1), restaurant workers employed at an establishment in a DeSO with 10% more residents predicted to work from home would see a relative improvement in earnings of about 153 SEK (∼15 USD) in the post-COVID period and about 180 SEK (∼17 USD) in the COVID period, on average. This tracks with our expectation that the effects on workers earnings would mimic the effect of restaurant production, since the establishments seeing a relative increase in sales would be the same restaurants to need workers to work more hours and have a relatively larger surplus to split with workers. We see even larger effects for the subset of tenured workers. When we include the predicted WFH for workers, we find little effect for workers' predicted WFH and similar effects for residents' predicted WFH in the post-COVID period. However, we find mixed results for the COVID period, with predicted WFH for workers the dominant effect in the full sample, but predicted WFH for residents to dominant effect for the tenured worker sample. These different effects during the COVID period could be driven by the large decrease in employment for workers at restaurants in more working areas.

We then dig into whether the differential earnings effects are driven by a persistence of COVID-19 policy. These results can be found in Table B.4. Similar to our restaurant sales results, we find no effect of differential exposure to COVID-19 policies on earnings when looking at the deaths of residents. However, we do find significant differential effects when looking at COVID-related deaths for workers in the region, however they are economically insignificant. Since the share of deaths among workers is very small (ranging from 0 to 0.075 deaths per 100 workers) these estimates equate to only an upper bound relative increase in earnings of 45.37 SEK (∼4.36 USD) for the post-period and 32.82 SEK (∼3.15 USD) for the COVID period on average, which is a negligible difference.[11]

5.2.3 Commuting

Along with earnings, restaurant workers may faces changes in commuting times due to the geographic shifting of restaurant production and the increasing levels of WFH. If firms are moving towards residential areas where restaurant workers live, they may face shorter commutes. However, if they are moving to residential areas where there is high WFH potential, but not where the restaurant workers live, they may be facing longer commutes. The results for changes in restaurant worker commuting can be found in Table 8.

There seems to be no effect on commuting that we can determine in our data. We find no significant differential effect on the commuting distance for restaurant workers in either the COVID period or post-COVID period when compared to the pre-COVID period and the point estimates are economically insignificant. Estimates for the alternative specifications using log commuting distance at the worker level and using a binary measure of the percentage of workers that live and work in the same DeSO at the neighborhood level are equally insignificant and close to 0. This pattern of no statistical difference in commuting holds even when we look at differential effects by predicted WFH (Table B.5) and COVID exposure (Table B.6) holding residential weight constant. These insignificant effects suggest that there is no differential residential sorting of restaurant workers, at least in the short post-COVID period we investigate.

[11]By *upper bound* here, we are using the upper bound of the estimated 95% confidence interval for the average effect to compare the difference in earnings for the DeSO with the fewest (0) and highest (0.0175) COVID deaths per 100, unconditional on their residential weight.

Table 8: Effect of residentiality on commuting distance for restaurant workers (2019-2021)

	Commuting Distance (meters)	Commuting Distance (logs)	% Same DeSO to work and live
RW x Post-period	1.105	-0.000	0.003
	(14.344)	(0.002)	(0.003)
RW x COVID-period	4.029	-0.001	0.000
	(10.865)	(0.001)	(0.002)
Individual F.E.	Y	Y	N
DeSO-level F.E.	N	N	Y
Month-year F.E.	Y	Y	Y
R^2	0.00	0.00	0.00
N	3,312,371	3,054,018	129,122

Note: The data in these specifications only span from 2019-2021. Columns 1 and 2 are estimated at the individual worker level while column 3 is estimated at the DeSO level. Commuting distance is measured in meters in column 1 and in logs in column 2. Column 3 represents the share of workers in that DeSO that also live in the DeSO (they work and live in the same DeSO). "RW" is an abbreviation for the residential weights. Residential weights are fixed at the 2016 level. Standard errors are clustered at the Individual-level for columns 1 and 2 and are clustered at the DeSO-level for column 3.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6 Conclusion

Changes in working and mobility patterns brought about by WFH has large impacts on economic and spatial structure that extend beyond the realm of industries directly capable of WFH. Those effects became even more prominent and relevant with the recent COVID-19 pandemic, which led to a large and persistent increase in WFH take up. In this paper, we investigate the effects of an increase in WFH on the spatial structure of cities specifically through a change in the geographic distribution of production of restaurants. Using COVID-19 as an exogenous shock, we find that more residential neighborhoods saw relatively higher restaurant sales than restaurants in more working areas not just during the peak of the pandemic, but extending into the post-pandemic period. This result is robust to different ways of structuring our sample as well as to the inclusion of prominent demographic characteristics, indicating that some aspect of the pandemic has triggered a geographic shift in consumption.

When digging into the mechanisms, we are able to disentangle the effect from an increase in WFH from other relevant COVID-19 consquences. We find that WFH is a major driver of this effect on restaurant production as neighborhoods with higher predicted WFH for residents seeing relatively higher restaurant sales, even holding the residentiality of the neighborhood constant. This suggests that these shifting consumption patterns are originating from workers going to the office less often and thus spending less on restaurants near their place of work and more on restaurants near where they live. Through this result, we provide some early empirical evidence of long-term spatial reorganization due to workers spending more time near their homes and less time at their offices. We also look into the role that COVID-19 directly plays in these persistent consumption changes. We find no evidence that greater exposure to COVID-19 diferentially affected the spatial distribution of restaurant consumption suggesting that these changes arose due to a general shift-in-norms that affected neighborhoods uniformly.

With prominent geographic changes in restaurant production, we should see effects on the restaurant labor market as well. We therefore follow up our spatial analysis by looking at the effects on labor market outcomes for restaurant workers. While we find some differential employment effects during the peak of the pandemic, these effects seemed to have leveled out by the post-pandemic period suggesting no persistent effect on employment. However, we do find a post-pandemic effect on earnings with workers in more residential areas earning relatively more, likely driven by more hours worked since employment is flat and demand has increased in these areas relative to more working areas. While restaurant workers seem to be working more, we do not find any change in their commuting patterns, indicating that neither residential sorting by restaurant workers nor alternate hiring practices by restaurants based on geographic area seems to be occurring, at least in the short post-period we explore.

There are a couple caveats about our results that should be consider. First, in the current version of this paper, post-period data is somewhat limited, particularly for the labor market outcomes of restaurant workers. Although we believe our results point towards actual persistent patterns, these limitations need to be considered when interpreting the results. In future versions of this paper, we will have longer a post-COVID time period which will allow us to test the persistent trends more thoroughly. A second caveat to consider relates to our results on commuting. While we believe comparing the distance between centroids of DeSOs acts as a good proxy for commuting distance, we do not have the data on the exact locations of restaurants or workers' homes so we cannot map out actual commuting paths. Therefore, our commuting results cannot capture small changes in commuting that may have arisen.

Our results open the door to further research. First, we focus our analysis on local service industries, which is unlikely to be the only non-remote industries affected by the increase in WFH. Further research into other industries can help to understand the overall effect of WFH. To that end, we also only explore partial equilibrium effects, but there are likely important general equilibrium effects that characterize the long term trend.

[Note: we have more data incoming so we will have results for a longer post-period and the results for the local service industries by the time of the conference.]

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A Additional Data Descriptions

A.1 Timeline of Relevant COVID-19 Policies in Sweden

- First confirmed case: January 31, 2020
- No full government lockdown
- Restrictions on restaurants and bars
  - Physical distancing and related measures – March 24, 2020 - September 29, 2021
  - No groups of more than 8 (4) people – November 3, 2020 - May 12, 2021 (December 24, 2020 - February 7, 2021)
  - Ban on alcohol sales after 10pm (8pm) – November 11, 2020 - April 11, 2021 (December 18, 2020 - February 28, 2021)
  - Capacity limit – December 18, 2020 - September 29, 2021
- Other relevant regulations and recommendations:
  - Banning of large public gatherings – March 2020 - September 2021
  - Recommendation that everyone who can WFH does – March 2020 - September 2021
  - Recommendation that upper secondary schools & universities move to distance learning – March - May 2020; December 2020 - June 2021
  - Avoid public transportation – June 2020 - September 2021
- Almost all (relevant) restrictions/recommendations are removed by the end of September 2021

A.2 Worker-Establishment Inclusion Criteria

Here we discuss in more detail the data surrounding workers having multiple establishments per month and the criteria we used to limit workers to one plant per month.

1. All worker-establishment-month observations where there is 0 earnings or blank earnings are dropped as they are assumed to be unemployed in that period.
2. Keep only the worker-establishment-month observations where that worker received the highest earnings in that month (all highest earnings and single establishment per month are kept as well as multiple establishments that are listed giving the same earnings).
3. For the remaining observations that have multiple establishments per month, keep the first if the Plant DeSO is the same for all these establishments since it is aggregated up anyway.

4. For the remaining observations that have multiple establishments per month, drop any observations where the establishment cannot be matched to a Plnat DeSO since they cannot be used anyway.

5. For the remaining observations that have multiple establishments per month, keep only the observations where the establishment's Plant DeSO corresponds to the most common Plant DeSO for all the establishments where that worker worked in that calendar year.

6. For any remaining worker-month observations that are still associated with multiple establishments, keep the first one (only 19, 14, and 28 workers are affected by this in 2019, 2020, and 2021, respectively).

A.3 Additional Descriptives

Table A.1: Annual descriptive statistics - 2016
(B- and C-type DeSOs)

	Quartile 1 (most working)	Quartile 4 (most residential)	All
Average restaurant total sales per person	2.48	0.15	0.85
Average restaurant food sales per person	1.87	0.13	0.65
Average restaurant alcohol sales per person	0.57	0.02	0.19
Average residents per DeSO	1,712	1,772	1,740
Average workers per DeSO	2,679	169	1,073
Average restaurant plants per DeSO	7.71	1.28	3.39
Average number of passenger cars	645	628	662
Average monthly income (SEK)	2,978	1,831	2,366
Average age	42	45	44
Average share female	0.48	0.51	0.52
Average share with a partner	0.88	0.89	0.88
Average share with children	0.37	0.35	0.36
Average share with at least tertiary education	0.33	0.33	0.32
N	1,226	1,226	4,904

Notes: These descriptive statistics are based on 2016 data and are averages across the DeSO-level statistics. Time-invariant variables are removed from this table, as they are the same as the 2019 statistics presented in Table 1. Commuting, earnings, and employment for restaurant workers are also removed since the data used to construct these variables begins in 2019. These descriptive statistics include all establishments but only the DeSOs in the "B" and "C" categories (we removed rural neighborhoods). Quartile 1 and Quartile 4 are the lowest and highest quartiles by 2016 Residential Weight, with Quartile 1 being the least residential and Quartile 4 being the most.

B Additional Tables

B.1 Additional Results Tables

Table B.1: Effect of WFH prediction and residentiality on restaurant employment

	Residents		Workers	
	Number of workers	Log employment	Number of workers	Log employment
RW x Post-period x resident-WFH	0.095	0.003*	-0.171*	-0.001
	(0.109)	(0.002)	(0.102)	(0.002)
RW x Post-period x worker-WFH			0.288**	0.004***
			(0.119)	(0.002)
RW x COVID-period x resident-WFH	0.543**	0.002*	-0.194*	-0.002
	(0.213)	(0.001)	(0.107)	(0.002)
RW x COVID-period x worker-WFH			0.802***	0.005***
			(0.223)	(0.001)
DeSO-level F.E.	Y	Y	Y	Y
Month-year F.E.	Y	Y	Y	Y
R^2	0.16	0.24	0.16	0.00
N	176,544	129,225	176,544	129,225

Note: The data in this specification only spans from 2019-2021. Results for employment are presented both in terms of actual number of workers and as log number of workers. "RW" is an abbreviation for the residential weights. "resident-WFH" is calculated as the mean of the WFH prediction probability for DeSO residents (all columns) and "worker-WFH" is the equivalent for workers (columns 3 & 4). They are both based on out-of-sample predictions using G-SWA survey responses for France, Germany, and the Netherlands. Residential weights are fixed at the 2016 level. Standard errors are clustered at the DeSO-level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.2: Effect of COVID exposure and residentiality on restaurant employment

	Residents		Workers	
	Number of workers	Log employment	Number of workers	Log employment
RW x Post-period x COVID-deaths	6.164*	-0.034	-15.114**	-0.160
	(3.707)	(0.078)	(5.956)	(0.262)
RW x COVID-period x COVID-deaths	6.873	0.056	-23.081***	-0.195***
	(5.347)	(0.054)	(5.924)	(0.187)
DeSO-level F.E.	Y	Y	Y	Y
Month-year F.E.	Y	Y	Y	Y
R^2	0.07	0.08	0.07	0.08
N	176,544	129,225	176,544	129,225

Note: The data in this specification only spans from 2019-2021. Results for employment are presented both in terms of actual number of workers and as log number of workers. "RW" is an abbreviation for the residential weights. "COVID-deaths" are calculated as the percentage of the DeSO population that died over the whole COVID period for residents (columns 1 & 2) and workers (columns 3 & 4) in the DeSO. Residential weights are fixed at the 2016 level. Standard errors are clustered at the DeSO-level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.3: Effect of WFH prediction and residentiality on restaurant workers' earnings

	Residents		Workers	
	Full Sample	Tenured Workers	Full Sample	Tenured Workers
RW x Post-period x resident-WFH	15.93***	31.37***	17.43***	31.16*
	(4.65)	(10.73)	(6.37)	(16.07)
RW x Post-period x worker-WFH			-1.87	1.88
			(4.72)	(11.62)
RW x COVID-period x resident-WFH	18.04***	33.25***	5.16	16.67**
	(2.77)	(5.53)	(3.58)	(7.52)
RW x COVID-period x worker-WFH			12.20***	15.30
			(2.87)	(5.97)
Individual F.E.	Y	Y	Y	Y
Month-year F.E.	Y	Y	Y	Y
R^2	0.00	0.00	0.00	0.00
N	3,337,706	462,647	3,337,706	462,647

Note: In this table, we present results for only earnings in levels. We present the results for the full sample of workers (columns 1 and 3) and for tenured workers (columns 2 and 4). "Tenured workers" is the subset of workers that remained in the same establishment for all of 2019-2021. The data in this specification only spans from 2019-2021. "RW" is an abbreviation for the residential weights. "resident-WFH" is calculated as the mean of the WFH prediction probability for DeSO residents (all columns) and "worker-WFH" is the equivalent for workers (columns 3 & 4). They are both based on out-of-sample predictions using G-SWA survey responses for France, Germany, and the Netherlands. Residential weights are fixed at the 2016 level. Standard errors are clustered at the Individual-level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.4: Effect of COVID exposure and residentiality on restaurant workers' earnings

	Residents		Workers	
	Full Sample	Tenured Workers	Full Sample	Tenured Workers
RW x Post-period x COVID-deaths	186.80	48.39	1,779.29**	2,126.15
	(193.63)	(431.66)	(813.27)	(2,132.56)
RW x COVID-period x COVID-deaths	46.18	331.98	1,387.88***	1,967.32**
	(111.27)	(205.16)	(487.58)	(879.38)
Individual F.E.	Y	Y	Y	Y
Month-year F.E.	Y	Y	Y	Y
R^2	0.00	0.00	0.00	0.00
N	3,336,969	462,588	3,336,969	462,588

Note: In this table, we present results for only earnings in levels. We present the results for the full sample of workers (columns 1 and 3) and for tenured workers (columns 2 and 4). "Tenured workers" is the subset of workers that remained in the same establishment for all of 2019-2021. The data in this specification only spans from 2019-2021. "RW" is an abbreviation for the residential weights. "COVID-deaths" are calculated as the percentage of the DeSO population that died over the whole COVID period for residents (columns 1 & 2) and workers (columns 3 & 4) in the DeSO. Residential weights are fixed at the 2016 level. Standard errors are clustered at the Individual-level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.5: Effect of WFH prediction and residentiality on commuting distance for restaurant workers

	Residents	Workers
	Commuting Distance	Commuting Distance
RW x Post-period x resident-WFH	-3.900*	-4.803*
	(2.031)	(2.751)
RW x Post-period x worker-WFH		0.817
		(2.108)
RW x COVID-period x resident-WFH	-2.822*	-2.689
	(1.514)	(2.087)
RW x COVID-period x worker-WFH		-0.385
		(1.602)
Individual F.E.	Y	Y
Month-year F.E.	Y	Y
R^2	0.01	0.01
N	3,312,371	3,312,371

Note: The data in this specification only spans from 2019-2021. Commuting distance is measured in meters. "RW" is an abbreviation for the residential weights. "resident-WFH" is calculated as the mean of the WFH prediction probability for DeSO residents (both columns) and "worker-WFH" is the equivalent for workers (column 2). They are both based on out-of-sample predictions using G-SWA survey responses for France, Germany, and the Netherlands. Residential weights are fixed at the 2016 level. Standard errors are clustered at the Individual-level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.6: Effect of COVID exposure and residentiality on commuting distance for restaurant workers

	Residents	Workers
	Commuting Distance	Commuting Distance
RW x Post-period x COVID-deaths	67.460	-193.118
	(90.557)	(344.992)
RW x COVID-period x COVID-deaths	24.700	-341.290
	(69.468)	(259.279)
Individual F.E.	Y	Y
Month-year F.E.	Y	Y
R^2	0.00	0.00
N	3,311,649	3,311,649

Note: The data in this specification only spans from 2019-2021. Commuting distance is measured in meters. "RW" is an abbreviation for the residential weights. "COVID-deaths" are calculated as the percentage of the DeSO population that died over the whole COVID period for residents (column 1) and workers (column 2) in the DeSO. Residential weights are fixed at the 2016 level. Standard errors are clustered at the Individual-level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B.2 Robustness Checks

Table B.7: Restaurant sales specifications with alternate definitions of time periods

	Main	WFH prediction		COVID exposure	
		Residents	Workers	Residents	Workers
RW x Post-period	0.038***				
	(0.014)				
RW x COVID-period	0.083***				
	(0.011)				
RW x Post-period x WFH prediction		0.005***	0.002		
		(0.002)	(0.001)		
RW x COVID-period x WFH prediction		0.006***	0.006***		
		(0.001)	(0.001)		
RW x Post-period x COVID-deaths				0.022	-0.050
				(0.084)	(0.226)
RW x COVID-period x COVID-deaths				0.080	-0.124
				(0.078)	(0.204)
DeSO-level F.E.	Y	Y	Y	Y	Y
Month-year F.E.	Y	Y	Y	Y	Y
R^2	0.08	0.06	0.07	0.08	0.08
N	321,489	321,489	321,489	321,489	321,489

Note: In these specifications, the COVID period is defined as all of 2020 and 2021 and the post-COVID period is defined as all of 2022. Here we show the results for the full sample of firms. Column 1 corresponds to the results from Column 1 in Table 2, Columns 2 and 3 correspond to the results from Columns 1 and 3 of Table 4, and Columns 4 and 5 correspond to Columns 1 and 3 of Table 5. "RW" is an abbreviation for the residential weights and are fixed at the 2016 level. Standard errors are clustered at the DeSO-level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.8: Restaurant sales specifications including rural DeSOs

	Main	WFH prediction		COVID exposure	
		Residents	Workers	Residents	Workers
RW x Post-period	0.030**				
	(0.012)				
RW x COVID-period	0.109***				
	(0.011)				
RW x Post-period x WFH prediction		0.004***	0.002*		
		(0.002)	(0.001)		
RW x COVID-period x WFH prediction		0.007***	0.006***		
		(0.001)	(0.001)		
RW x Post-period x COVID-deaths				0.011	0.161
				(0.072)	(0.208)
RW x COVID-period x COVID-deaths				0.069	-0.104
				(0.085)	(0.202)
DeSO-level F.E.	Y	Y	Y	Y	Y
Month-year F.E.	Y	Y	Y	Y	Y
R^2	0.08	0.04	0.05	0.07	0.07
N	370,934	370,934	370,934	370,934	370,934

Note: In these specifications, we include all DeSOs in our sample, including the rural ("A" type) DeSOs that we drop in the main specification. Here we show the results for the full sample of firms. Column 1 corresponds to the results from Column 1 in Table 2, Columns 2 and 3 correspond to the results from Columns 1 and 3 of Table 4, and Columns 4 and 5 correspond to Columns 1 and 3 of Table 5. "RW" is an abbreviation for the residential weights and are fixed at the 2016 level. Standard errors are clustered at the DeSO-level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.9: Restaurant sales specifications for only single-plant firms

	Main	WFH prediction		COVID exposure	
		Residents	Workers	Residents	Workers
RW x Post-period	0.044***				
	(0.012)				
RW x COVID-period	0.120***				
	(0.011)				
RW x Post-period x WFH prediction		0.005***	0.001		
		(0.002)	(0.001)		
RW x COVID-period x WFH prediction		0.007***	0.006***		
		(0.002)	(0.001)		
RW x Post-period x COVID-deaths				0.015	0.059
				(0.073)	(0.207)
RW x COVID-period x COVID-deaths				0.136	-0.170
				(0.084)	(0.209)
DeSO-level F.E.	Y	Y	Y	Y	Y
Month-year F.E.	Y	Y	Y	Y	Y
R^2	0.08	0.05	0.07	0.08	0.08
N	317,583	317,583	317,583	317,583	317,583

Note: In these specifications, we include only firms that have exactly one establishment and drop all multi-establishment firms to check how sensitive our results are to our firm sales allocation method. Here we show the results for the full sample of firms. Column 1 corresponds to the results from Column 1 in Table 2, Columns 2 and 3 correspond to the results from Columns 1 and 3 of Table 4, and Columns 4 and 5 correspond to Columns 1 and 3 of Table 5. "RW" is an abbreviation for the residential weights and are fixed at the 2016 level. Standard errors are clustered at the DeSO-level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.10: Restaurant sales specifications with alternate COVID exposure variables

	Confirmed COVID deaths		COVID cases		Symptomatic COVID cases		COVID ICU admittance	
	Residents	Workers	Residents	Workers	Residents	Workers	Residents	Workers
RW x Post-period x COVID-deaths	0.018	0.046	-0.008	-0.010**	-0.013**	-0.008*	-0.208**	-0.014
	(0.073)	(0.208)	(0.007)	(0.005)	(0.006)	(0.004)	(0.088)	(0.087)
RW x COVID-period x COVID-deaths	0.101	-0.122	0.000	-0.008**	-0.012**	-0.011***	-0.167*	-0.127
	(0.087)	(0.209)	(0.006)	(0.004)	(0.005)	(0.004)	(0.092)	(0.079)
DeSO-level F.E.	Y	Y	Y	Y	Y	Y	Y	Y
Month-year F.E.	Y	Y	Y	Y	Y	Y	Y	Y
R^2	0.08	0.08	0.07	0.07	0.07	0.07	0.07	0.07
N	321,489	321,489	321,489	321,489	321,489	321,489	321,489	321,489

Note: In these specifications, we use alternate variables to proxy for COVID exposure. We show the results for the full sample of firms. "Confirmed COVID deaths" only includes deaths that returned a positive result on a COVID-19 test. "COVID cases" is the total number of confirmed COVID cases. "Symptomatic COVID cases" includes only the cases where the testing reason was listed as "symptoms." "COVID ICU admittance" is the instances where an individual was admitted to the ICU because they had COVID or because they had COVID-related symptoms or illnesses. All of these variables are calculated as the total in 2020 and 2021 and calculated separately for the residents and workers in the DeSO per 100 residents or workers, respectively. Specifications are run separately for the residents and workers. These results correspond to the specification in equation 3 and are comparable to Columns 1 and 3 of Table 5. "RW" is an abbreviation for the residential weights and are fixed at the 2016 level. Standard errors are clustered at the DeSO-level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B.3 WFH prediction results

Table B.11: Logit on "ever work from home" (binary)

Variable	Prediction Weight
Age (Continuous)	-0.02
Gender (Binary 1 = Male)	-0.13
Education (1 = Tertiary)	0.81
Education (2 = Graduate)	1.54
Married (Binary)	0.19
Has Kids (Binary)	0.28
Industries (Agriculture, Forestry, Fishing, and Hunting is omitted)	
Banking, Finance, Insurance	2.27
ICT	2.10
Retail, Rental, and Leasing Services	1.42
Professional, Technical, and Business Services	1.40
Government (Public Sector)	1.29
Education	1.18
Mining, Quarrying, and Gas/Oil Extraction	1.02
Utilities	0.89
Arts, Entertainment, and Recreation	0.77
Other Industries	0.57
Construction	0.46
Wholesale and Retail Trade	0.28
Transportation and Warehousing	0.18
Accommodation, Hospitality, and Food Services	0.17
Manufacturing	0.16
Heath Care and Social Assistance	-0.18
Constant	-0.93

Note: Out-of-sample WFH prediction is based off of the results from respondents from France, Germany, and the Netherlands on both Wave 1 (July-August 2021) and Wave 2 (January-February 2022) of the Global Survey of Working Arrangements (Aksoy et al. (2022)). Prediction accuracy for Swedish results from that survey is approximately 67%. The categories for the education and industry variables are redefined from the original survey in order to match the classifications in our Swedish data.

B.4 Pre-trends Tests

Table B.12: Pre-trend test

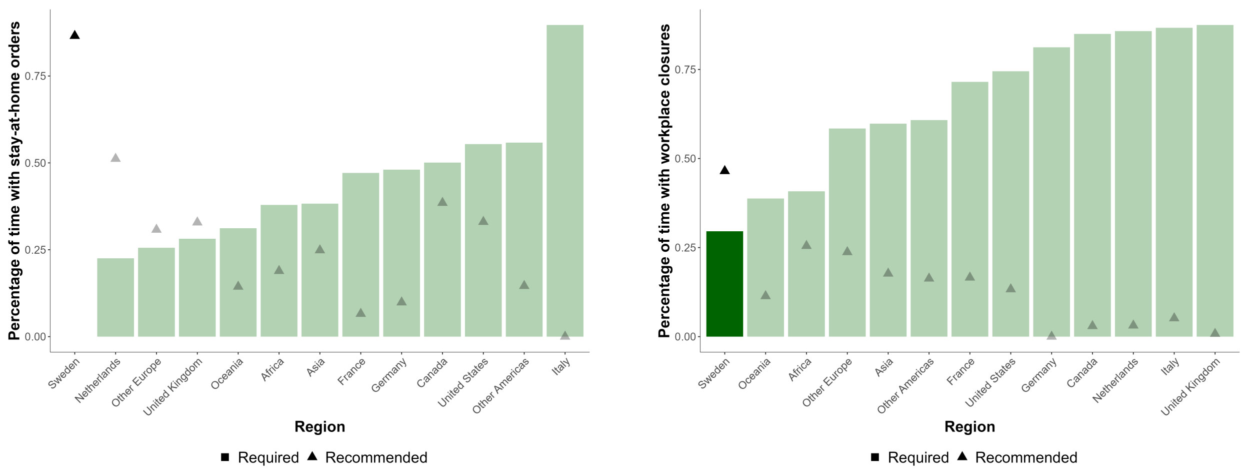
	Granger-type causality test
RW × Post-period	0.028*
	(0.015)
RW × COVID-period	0.105***
	(0.013)
RW × Year-2019	-0.004
	(0.012)
RW × Year-2018	0.000
	(0.010)
RW × Year-2017	-0.005
	(0.008)
Post-period	0.054***
	(0.016)
COVID-period	-0.015
	(0.014)
Year-2019	0.125***
	(0.012)
Year-2018	0.078***
	(0.010)
Year-2017	0.038***
	(0.008)
Constant	6.356***
	(0.007)
DeSO-level F.E.	Y
Month-year F.E.	Y
R^2	0.03
N	321,489

Notes: This specification presents the estimated coefficients for the Granger-type causality test run to check for possible differential linear trends in the pre-period by residential weight. "RW" is an abbreviation for the residential weights and are fixed at the 2016 level. Standard errors are clustered at the DeSO-level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C Additional Figures

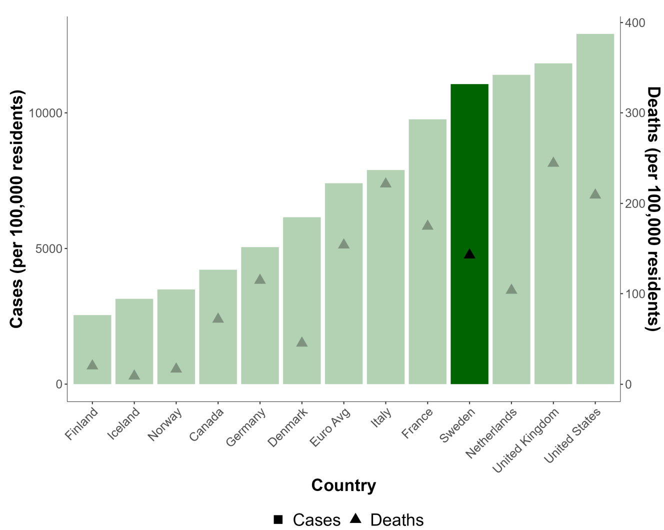
Figure C.1: Comparison of COVID-19 policy measures (over the COVID period)

(a) Percentage of days with stay-at-home orders (b) Percentage of days with workplace closures



Notes: For both panels, we look at the share of days with certain COVID-19 policies from January 1, 2020 through September 30, 2021. The bars represent the percentage of days over that period where the policy was "required" and the triangles represent the percentage of days where the policy was "recommended." For panel (a), "Required" is the sum of both "Required to not leave the house with exceptions" and "Required to not leave the house without exceptions." Sweden never had required stay-at-home orders, so there is no bar for Sweden. For panel (b), "Required" is the sum of both "Required for some" and "Required for all but essential occupations." Sweden is colored in dark for easy identification.
Source: Hale et al. (2021); processed by Our World in Data

Figure C.2: Cumulative COVID-19 cases and deaths per 100,000 residents at September 29, 2021

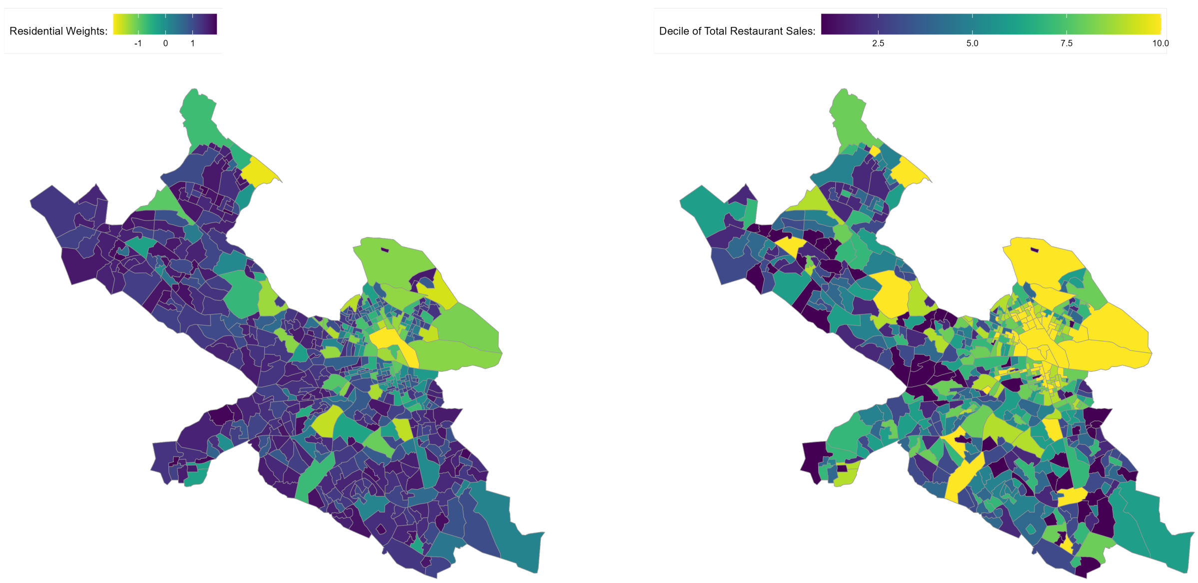


Notes: The bars show the number of cases per 100,000 residents for 29, 2021 (the day most restrictions/recommendations were removed for Sweden) and use the left axis scale. The triangles show the deaths per 100,000 residents for September 29, 2021 and use the right axis scale. Sweden is colored in dark green for easy identification. The COVID-19 data comes from the World Health Organization and the 2019 population data comes from the World Bank.
Sources: World Health Organization (2023); World Bank (2019)

Figure C.3: Sotckholm Municipality DeSOs - 2016

(a) Residential weights

(b) Decile of restaurant sales

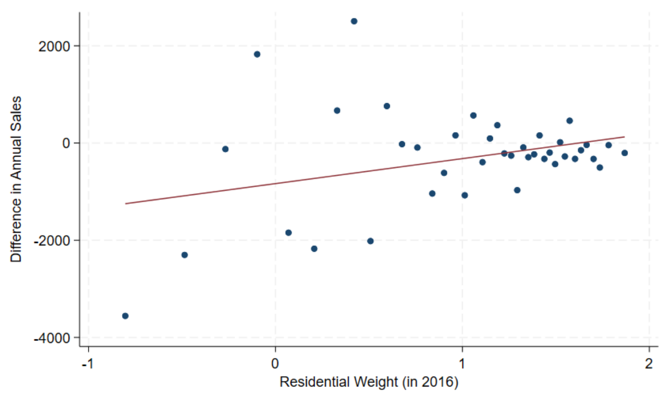


Notes: Both panels in this figure show the DeSOs for the Stockholm municipality. Panel (a) colors the DeSOs by 2016 residential weight with yellower (lighter) colors indicating more working neighborhoods and the bluer (darker) colors representing more residential neighborhoods. For context, the area in the center right (where there are more working DeSOs) is the primary central business district of Stockholm. Panel (b) presents the same map, but colors the DeSOs by decile of restaurant sales in 2016. Yellower (lighter) colored DeSOs are higher in terms of the decile of restaurant sales, while bluer (darker) DeSOs are lower in terms of the decile of sales. We use restaurant sales deciles instead of actual sales to remove skewing caused by outliers. The 2019 version of this figure is found in Figure 4.

Figure C.4: Change in residential weight from 2016 to 2019

Notes: In this figure, we plot the difference in residential weights (2019-2016) against 2016 residential weight. This figure shows that DeSOs were relatively stable over time with respect to their residentiality and that there is no obvious selection in the changes by residential weight.

Figure C.5: Difference in sales (2022-2019) by 2016 residential weight (outliers removed)



Notes: In this figure, we show the binned scatter plot of 2016 residential weight and the difference in sales between 2022 and 2019 with all DeSOs with a residential weight less than -1 removed. Total restaurant sales are measured in SEK. The red lines represent the estimated linear relationship. The original version of this figure is found in panel (b) of Figure 5.