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The Future of Work and Consumption in Cities after the Pandemic: Evidence from Germany

Abstract

We estimate the impact of working from home (WFH) on the micro-geography of offline consumer spending in urban agglomerations. Our analysis draws on micro-geographic card-transaction data and WFH patterns in German cities between January 2019 and May 2022. We use a difference-in-differences design that exploits the spatially differential exposure to the WFH shock induced by Covid-19 through the local scope to expand WFH. Our estimates suggest that local spending increases by 2–3 percent per standard deviation higher pre-pandemic untapped WFH potential. These effects hold after the permanent lifting of pandemic restrictions, indicating persistent relocations of offline consumption within cities.

JEL-Codes: D100, E200, G200, J000.

Keywords: work from home, consumer spending, urban agglomerations, cities, micro-spatial analysis.

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1. Introduction

The Covid-19 pandemic has disrupted traditional work organization by inducing a sudden and lasting shift towards working from home (WFH) (Barrero et al., 2021a,b; Aksoy et al., 2022).[1] The resulting transformation of the geography of work carries the potential to fundamentally alter the distribution of economic activity in cities and even to challenge their "survival" (Florida et al., 2021; Glaeser and Cutler, 2021). Recent research documents significant changes in consumption patterns in cities (Chetty et al., 2020a,b; Chen et al., 2021; Alcedo et al., 2022) as well as a declining premium on proximity to urban centers in real estate prices during the pandemic and beyond (Ramani and Bloom, 2021; Rosenthal et al., 2021; Althoff et al., 2022; Gupta et al., 2022). However, the existing literature lacks causal evidence on the link between the new geography of work and economic activity within urban agglomerations.[2]

We fill this gap by empirically studying the effect of WFH on the micro-geography of offline consumer spending in cities. We draw on novel card-transaction data supplied by *Mastercard* and survey evidence on the prevalence of WFH at the postcode level for five major German metropolitan areas between January 2019 and May 2022. Our empirical framework exploits the spatially differential exposure to the WFH shock induced by Covid-19 within cities. The granularity and the precision of the data allow us to trace differences in local spending trends from 2019 through the permanent lifting of pandemic restrictions and link these to the severity of the WFH shock. We organize the analysis into two parts.

In the first part, we analyze spatial consumption shifts within urban agglomerations. We explore differential spending trends across metropolitan postcode areas with higher versus lower pre-crisis consumption intensity using a difference-in-differences (DiD) design. Consumption-intensive areas are typically located close to city centers, exhibit higher population and business density, and have more expensive housing. We find similar spending trends across all areas before the pandemic outbreak in March 2020, followed by a sudden spending drop in high relative to low consumption-intensity postcodes. The estimates imply that offline transaction volumes decline by 6-10 percent for every standard deviation increase in pre-Covid consumption intensity im-

[1] Additional evidence from job vacancy postings shows that job offerings are increasingly advertised with a WFH option (Alipour et al., 2021b; Bamieh and Ziegler, 2022). In the US, today's dominant work model for graduate employees is hybrid WFH with employees working some days at home and others in the office (Bloom et al., 2022).

[2] Other studies have assessed this question only implicitly (Chetty et al., 2020b), theoretically (Gokan et al., 2022; Kwon et al., 2022), or with a narrow spending definition (De Fraja et al., 2021, 2022).

mediately after the outbreak. The gap increases to nearly 15 percent in subsequent months and had not recovered by May 2022. The pattern is similar across different spending categories, including eating places, grocery and food stores, and apparel stores. A closer look at the data reveals that the effects are partly driven by an *absolute* spending increase in lower consumption-intensity areas, while consumption-intensive areas lose revenue throughout the post-outbreak period. Importantly, a distinguishing feature of lower consumption-intensity areas is stronger WFH growth during the pandemic. These observations motivate us to examine WFH as a key channel through which the pandemic shock altered the spatial distribution of offline consumption within cities.

In the second part, we investigate the causal link between regional changes in offline card transactions and differences in local WFH. The validity of our DiD design rests on the identifying assumptions that *i)* spending trends across postcode with high and low WFH growth are parallel except through the Covid-19 shock, and *ii)* that regional differences in WFH are exogenous. Since WFH uptake is unlikely to be orthogonal to other determinants of spending changes after the pandemic outbreak, the endogeneity of WFH poses a key challenge to identification. We address this problem in two steps. First, we estimate intention-to-treat (ITT) effects based on a measure of "untapped WFH potential", defined as the local share of employees with a teleworkable job who *did not* work from home before the pandemic. The measure thus approximates the scope to *expand* WFH at employees' area of residence after the outbreak relative to occupation-related feasibility (Alipour et al., 2022). Since untapped WFH potential is determined before the pandemic, it is unaffected by other sources of disruption to spending patterns and thus alleviates endogeneity concerns. The measure strongly predicts both observed WFH growth during the pandemic and projected growth rates based on employees' desires and employer plans for the post-Covid future. However, differences in untapped WFH potential may still be correlated with other determinants of spending changes. The fact that economic activity is unevenly distributed within cities may pose a threat to identification (Redding, 2022). If, for instance, non-essential businesses are more concentrated in areas with lower untapped WFH potential, then our estimates may pick up supply-side disruptions due to business closures rather than WFH effects. Behavioral adjustments to the Covid-19 shock may also bias our estimates to the extent that untapped WFH potential is correlated with local population structure. Our second step to address these problems is thus to dynamically control for local area characteristics that may be correlated both with untapped WFH potential and time trends. The most demanding specification controls for measures of pre-Covid economic activity, local industry composition, socioeconomic status of the population, age composition, and building use, each separately interacted with a full set of time indicators.

Our DiD estimates suggest that spending trends across postcodes with higher and lower untapped WFH potential are parallel before March 2020, supporting the validity of our first identifying assumption. Postcodes with greater scope to expand WFH experience a sharp relative increase in consumer spending immediately after the outbreak. The effects are significant for spending on business days (Monday-Friday) but small and insignificant for spending on Saturdays, consistent with WFH as the driving mechanism. The unconditional estimates are positive and significant throughout the post-outbreak period. However, once we account for other potential sources of spending disruptions, the effects of WFH become insignificant during lockdown periods, remaining sizable and significant only in non-lockdown periods and after pandemic restrictions are permanently lifted. The estimates suggest that consumer spending is on average 2–3 percent higher per one standard deviation increase in untapped WFH potential. We propose two explanations for this result. First, once we account for supply-side factors (e.g., local industry composition), WFH cannot generate regional spending shifts when most retail stores are closed across the economy; instead, we show that consumption shifts from offline to online commerce during lockdown periods. Second, as established by previous work, the ability to work from home is *negatively* correlated with job loss and short-time work during the pandemic (Adams-Prassl et al., 2020; Alipour et al., 2021a). This leads to a situation in which WFH effects are attenuated as both remote workers and employees on short-time work stay at home during periods of heavy containment measures.

Our findings have important implications for the future of cities. There is growing consensus that WFH will stick in the post-pandemic economy. Our representative survey projects that 24 percent of workers will WFH at least partly in the future. Recent evidence from the United States and Germany suggests that WFH has already stabilized at this level (Bloom et al., 2022; ifo Institute for Economic Research, 2022a,b,c). Thus, we project that the spatial shifts in consumption induced by WFH and observed until May 2022 are here to stay.

2. Postcode-Level Data on Consumer Spending and WFH

Sample. Our sample comprises postcode-level observations for the broadly-defined metropolitan areas of five major German cities: Berlin (5.2 million inhabitants), Hamburg (3.1 million), Munich (2.6 million), Stuttgart (2.2 million), and Dresden (1.2 million), which together cover about 17 percent of Germany's total population. The metro areas are located in different parts of Germany and constitute the regional centers of their respective geographies. We observe daily consumer spending between January 2019 and May 2022, local area characteristics, as well as WFH uptake before and during the pandemic and expectations for the post-Covid future. The time period under investigation includes the outbreak of the Covid pandemic in Germany in March 2020 and two lockdowns (March–May 2020, and November 2020–May 2021).[3] Nearly all remaining Covid restrictions were lifted in March 2022.

Debit & Credit Card Transaction Data by Mastercard. We measure local offline consumer spending using anonymized and aggregated data on debit and credit card transactions provided by *Mastercard Retail Location Insights*.[4] Offline spending refers to transactions at brick-and-mortar stores, spanning different sectors, including among others, groceries and food stores, eating places, home improvement, apparel, hospitality, home furnishing, and consumer electronics. Transactions are aggregated from the point of sale (POS) to the postcode level and are available on a daily basis. We limit our sample to transactions with domestic cards to avoid distortions due to travel bans and international tourism. For confidentiality reasons, spending data for postcodes with few transactions and merchants in a given sector and day are set to missing. To ensure sufficient coverage over time, we limit the sample to postcodes with observations on at least five days per week in 2019 and focus our main analysis on *total* consumer spending. Our final sample includes 810 postcodes that we observe between 1 January 2019 and 31 May 2022.

WFH Survey & Local Characteristics by infas360. We complement the payment data with regional information on WFH patterns (measured at employees' place of residence) and area characteristics using representative survey data collected by *infas360*, a company specialized in micro-geographic survey and data-collection methods. We obtain postcode-level data from the spring 2022 wave of the infas360 CASA Monitor, a recurring online survey of roughly 11,000 individuals. We introduced a special set of questions about current and pre-Covid WFH frequency as well as employees'

[3]Lockdown periods were characterized by mandatory closures of non-essential businesses and other severe containment measures, including school closures and contact restrictions. From January through June 2021 as well as from November 2021 through March 2022, the containment measures required companies to offer WFH solutions to their employees conditional on the job profiles permitting remote work.

[4]In Germany, the volume share of all card payments – including debit and credit cards – represented about 48 percent of total consumer payments at points of sales (POS) in 2019 (ECB, 2020). In 2020, the share of card payments increased to 52 percent (ECB, 2021). Payments within the Mastercard network accounted for approximately 28 percent of total card payment volume (Statista, 2020).

desires and their employers' plans for the post-pandemic future. For improved data quality, an additional telephone survey was conducted with more than 1,000 participants. Furthermore, we include a broad range of information on socioeconomic characteristics, population characteristics, and area features compiled from surveys and administrative sources.

Summary statistics are reported in Table B.1 of the Appendix. The mean postcode size in our sample is 16,300 inhabitants. Figure A.1 of the Appendix presents a map of Germany highlighting the postcodes included in our sample.

3. Drivers of Spatial Changes in Offline Consumer Spending

3.1. Spending Trends by Local Consumption Intensity

While the pandemic outbreak was a plausibly exogenous event, differences in area characteristics mediate the severity of the shock to the local economy. A natural dimension across which to explore the evolution of spending patterns is the pre-crisis consumption intensity. Areas with high consumption intensity offer a high density of stores, provide amenities that attract a large number of consumers, and are often located close to city centers. Containment measures, including temporary business closures paired with behavioral responses to infection risk, are thus likely to disproportionately affect areas that attracted a greater level of offline consumption in the past. We formally analyze the differential impact of the Covid shock across high and low consumption-intensity areas by estimating the following dynamic difference-in-differences (DiD) specification:

$$Spending_{ct} = \sum_{k \neq Feb\_2020} \beta^k [\mathbb{1}(k = t) \times 2019\_Consumption\_Intensity_c] + \gamma_c + \delta_t + \epsilon_{ct}, \quad (1)$$

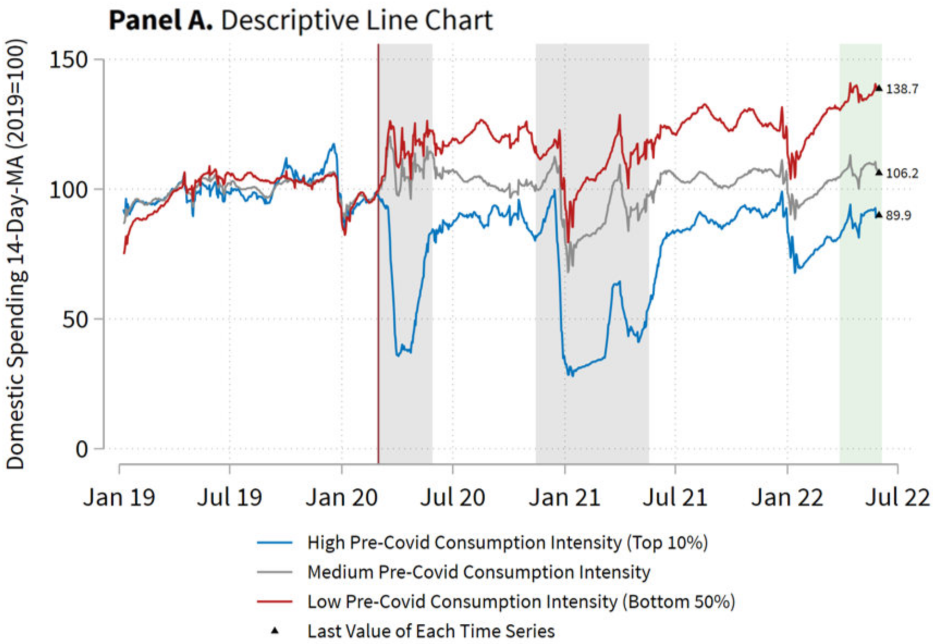
where $Spending$ is the log value of average daily offline consumer spending in postcode c and month t. 2019_$Consumption_Intensity$ denotes postcode c's pre-Covid consumption intensity measured on a continuous scale. Specifically, consumption intensity refers to the local volume of consumer spending in 2019 relative to the national average and is thus time-invariant. We standardize the measure to have mean zero and unitary standard deviation and include postcode and year-month fixed effects γ_c and δ_t, which absorb time-invariant determinants of spending and common time shocks. Hence, the coefficients β^k trace differences in spending associated with a one standard deviation higher pre-Covid consumption intensity over time. We use February 2020 as the reference period and cluster standard errors at the postcode level.[5]

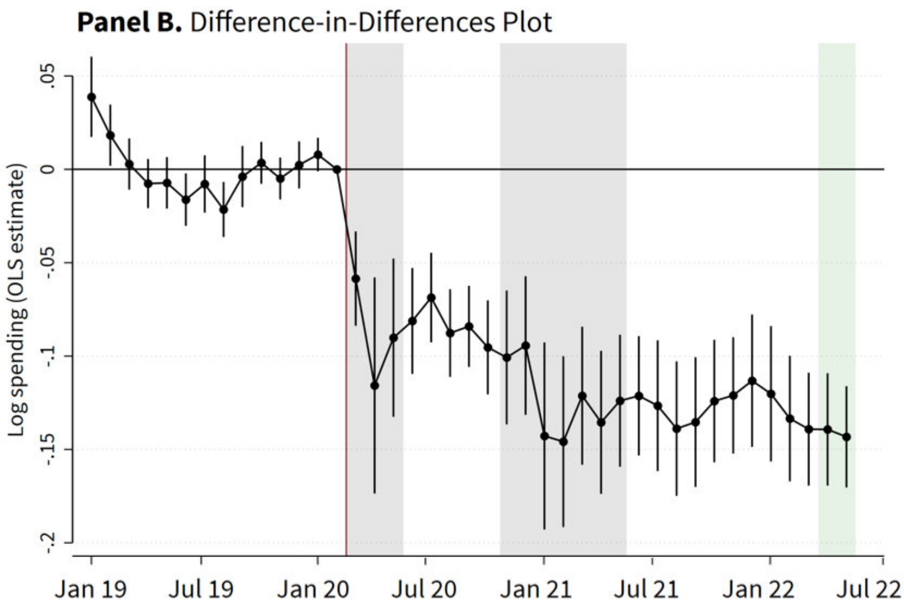
Before turning to the DiD results, Panel A of Figure 1 draws raw spending trends for postcodes grouped by high (top 10 percent), medium, and low (bottom 50 percent) consumption intensity in 2019. The time series are normalized by the 2019 average in each category to reflect percentage changes relative to pre-pandemic levels. In 2019, high consumption-intensity areas attracted 75 percent of consumer spending, while medium consumption-intensity postcodes accounted for almost 18 percent. By contrast, only 7 percent of spending occurred in low consumption-intensity areas. While trends are similar in the year before the pandemic outbreak in Germany, regional spending diverges significantly after February 2020. Transaction volumes in high consumption-intensity areas decline by 60 percent in the first lockdown, and by nearly 70 percent over the second lockdown (gray-shaded areas). Both lockdown periods were marked by mandatory closures of non-essential businesses and other strict containment measures. The trend recovers only partly between lockdown periods and reaches only 90 percent of the pre-crisis level after March 2022, when Covid restrictions were permanently lifted and nearly 80 percent of the population was vaccinated against Covid (green-shaded area). We find very similar trends for pedestrian frequency in consumption-intense high streets in our five cities under inspection (see Appendix Figure A.2, which shows the close co-evolution of consumer spending and pedestrian frequency). Trends in areas with a lower pre-crisis consumption intensity show a completely different picture. Transaction volumes *increase* in the first lockdown and remain above the pre-crisis level in nearly all periods after the outbreak. The most recent data point suggests that spending is 40 percent above the 2019 average. These spending trends are broad-based across sectors, as shown for the subcategories grocery and food stores, eating places, and apparel stores in Appendix Figure A.3.

The DiD coefficients $\hat{\beta}_k$ plotted in Panel B of Figure 1 complete the picture by giving insight into spending trends in more relative to less consumption-intensive areas. Pre-pandemic coefficients are small and largely statistically insignificant, with only a minor exception due to a seasonal effect around the turn of the year. Given our focus on the phase after the expiration of pandemic restrictions, which is not influenced by this seasonal deviation, the overall spending effects can be attributed to the conse-

[5] Alternative clustering of standard errors, e.g. at the postcode-month level or at city district categories to account for spatial spillovers, does not have a meaningful effect on the estimates.

Figure 1: Regional Association between Pre-Covid Consumption Intensity and Offline Consumer Spending





Notes: Panel A shows 14-day moving averages of daily offline spending in three categories of postcodes: high (top 10%), medium, or low (bottom 50%) 2019 consumption intensity. In each category, time series are normalized by the 2019 average. Panel B plots DiD estimates β^k on the interaction terms between standardized 2019 consumption intensity and monthly dummies (Equation 1). 95-percent confidence intervals are drawn using standard errors clustered at the postcode level. The vertical red line marks the outbreak of the Covid-19 pandemic between February and March 2020. The shaded gray areas highlight "lockdown" periods, characterized by closures of non-essential businesses and other severe containment measures. The shaded green area marks the period after March 2022, when nearly all restrictions have been lifted. The consumer spending data comprise domestic debit and credit card payments.

quences of the Covid shock rather than a pre-existing trend. The estimates imply that offline transaction volumes decline by about 12 percent for a one standard-deviation increase in pre-Covid consumption intensity in April 2020. The relative decline grows to nearly 15 percent in the second lockdown and does not recover by May 2022 (our latest data point). This shift is not merely driven by a change in the composition of spending across product segments or specific cities. Spending on different product segments declines in postcodes with high relative to low consumption intensity and shows no trend reversion in recent restriction-free months (see Appendix Figure A.4 for spending in the three product segments grocery and food stores, eating places, and apparel stores). In addition, the overall composition of consumer spending across all categories has remained stable over time, only with minor exceptions during lockdown periods (see Appendix Figure A.5). The spending effect is also not driven by a potential heterogeneity based on differential city size, with similar DiD results across large and medium-size cities (see Appendix Figure A.6). Still, a potential concern could be a behavioral change in consumers' preferred payment type from cash to cards. Since our empirical strategy yields estimates clean of such general time trends, only geographically heterogeneous shifts could be problematic. It is reassuring to note that estimates for the apparel industry, which already had a high share of card payments before the pandemic, are consistent with the overall results (Appendix Figure A.4), alleviating this concern. Our later estimations also control for factors such as local business composition to account for a potential heterogeneous take-up of card payments across different industries.

Taken together, the findings provide a first indication that the pandemic has permanently altered the micro-geography of consumption: offline spending gets withdrawn from previously popular destinations and relocated to less consumption-intensive areas. Simultaneously, a higher share of consumer spending is conducted online (see Appendix Figure A.7). Particularly during lockdown periods, when ubiquitous business closures preclude part of the usual offline spending, consumption shifted from offline to online commerce. The share of online spending displays conspicuous spikes during lockdown periods, reaching between 35 percent in 2020 to 40 percent in 2021, before stabilizing at an increased level of about 24 percent in 2022. This means that consumption-intensive postcodes lose twice: both in offline spending to less consumption-intensive areas and to spending on the Internet. In comparison, postcodes with previously low consumption intensity benefit overall, i.e., the loss to online spending is overcompensated by the spatial relocation of offline consumption in their favor.

While we are confident in attributing changes in spending to consequences of the pandemic, our results are so far silent about the *mechanisms* generating the observed trends. We characterize postcodes with a higher pre-Covid consumption intensity in Figure 2. Panel A estimates separate bivariate regressions of 2019 consumption intensity on postcode characteristics. Panel B presents OLS estimates from a multivariate regression using covariates selected by a first-stage Lasso regression. The results reveal that more consumption-intensive postcodes, on average, are less residential, have a greater share of working-age residents, higher cost of housing, higher population and business density, and a greater share of firms operating in finance and ICT. Thus, possible mediators of spending effects of the Covid-19 shock include supply-side factors, such as business closures and heterogeneous exposure to the pandemic due to different industry composition. Demand-side factors, such as regional differences in the adjustment of spending behavior due to heterogeneity in the composition of the local population may also play a role.

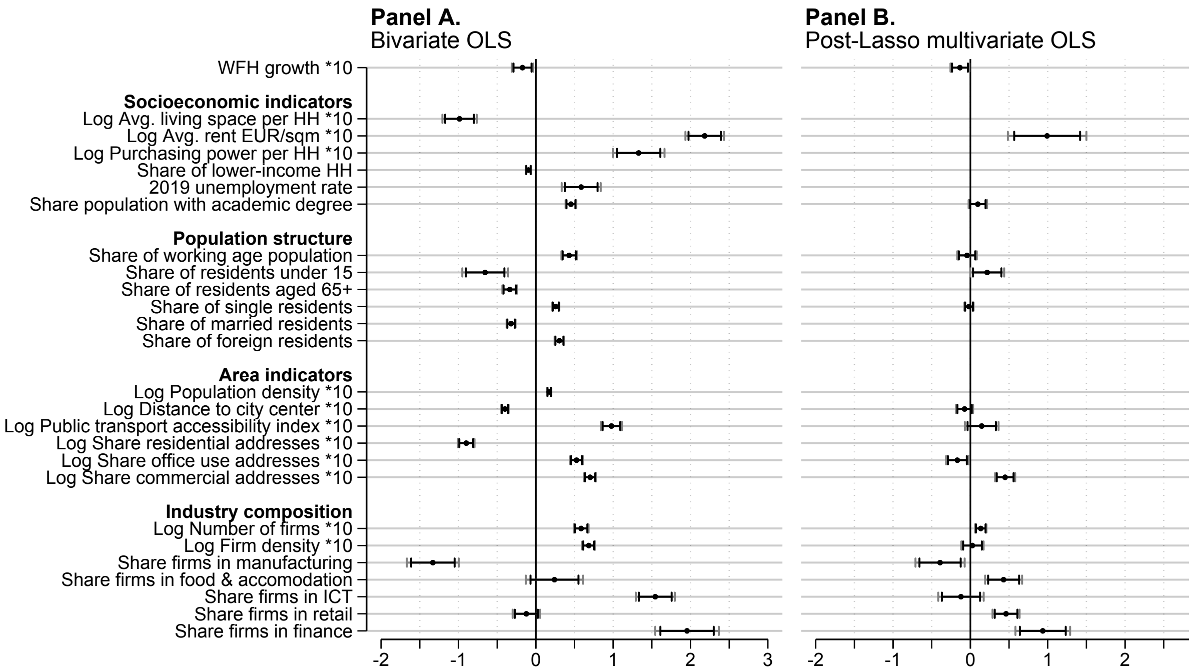
The correlates also show that consumption-intensive areas are located closer to city centers. On average, moving away from the city center by 10 percent reduces local (pre-Covid) consumption intensity by 4 percent. The negative correlation between distance and consumption intensity is also significant when looking at each metro area separately (see Appendix Figure A.8). The erosion of city centers mirrored by gains in more remote areas is consistent with the "donut effect", previously documented for the real estate market in major US cities during the pandemic (Ramani and Bloom, 2021). However, an important difference is that land use in big German cities is less segregated than in the US. German inner cities have residential areas close to shopping streets and many mixed-use structures, often combining office space, stores, and housing units. While city centers are hubs of offline consumption, consumption-intensive areas are not limited solely to city centers (see Appendix Figure A.9). Overall, in open periods in summers 2020, 2021 and May 2022, the strongest declines in spending are concentrated in the city centers, while most suburbs and surrounding areas experience an increase in spending relative to pre-Covid levels. This is true, especially in bigger cities such as Berlin. At the same time, the heterogeneity in land use within the city centers explains why a "donut" is not as clearly discernible.[6]

Interestingly, pre-crisis consumption intensity is also negatively correlated with WFH growth in February 2022 relative to pre-Covid levels. Thus, the upsurge of WFH

[6] Appendix Figures A.10–A.14 map local changes in total offline spending for summers 2020 and 2021 as well as May 2022 compared to the same period in 2019 for each metro area. Note that during these periods, Covid restrictions were limited and stores could open as usual.

during the pandemic constitutes another potential driver of regional spending shifts after 2020. Motivated by the evidence suggesting that WFH not only constituted a "mass social experiment" (Barrero et al., 2021b) during the crisis, but is also expected to persist in the post-pandemic future, we subsequently focus on this channel.

Figure 2: Correlates of Log 2019 Consumption Intensity



Notes: Panel A reports estimates from bivariate OLS regressions of log 2019 consumption intensity on postcode characteristics after partialling out metro-area fixed effects. Panel B shows the results of a multivariate OLS regression in which the covariates are selected by a Lasso regression including all covariates and choosing the penalty with a 10-fold cross-validation to minimize the mean squared error. Confidence intervals are heteroskedasticity-robust and drawn at the 90 and 95 percent levels.

3.2. Working From Home and Changes in Offline Consumer Spending

To establish a causal link between WFH and regional shifts in consumer spending, we draw on the DiD framework introduced in the previous section. One major challenge to identifying the effect of WFH on regional spending shifts is that WFH uptake after February 2020 is likely correlated with other sources of spending disruptions. We address this problem in two steps.

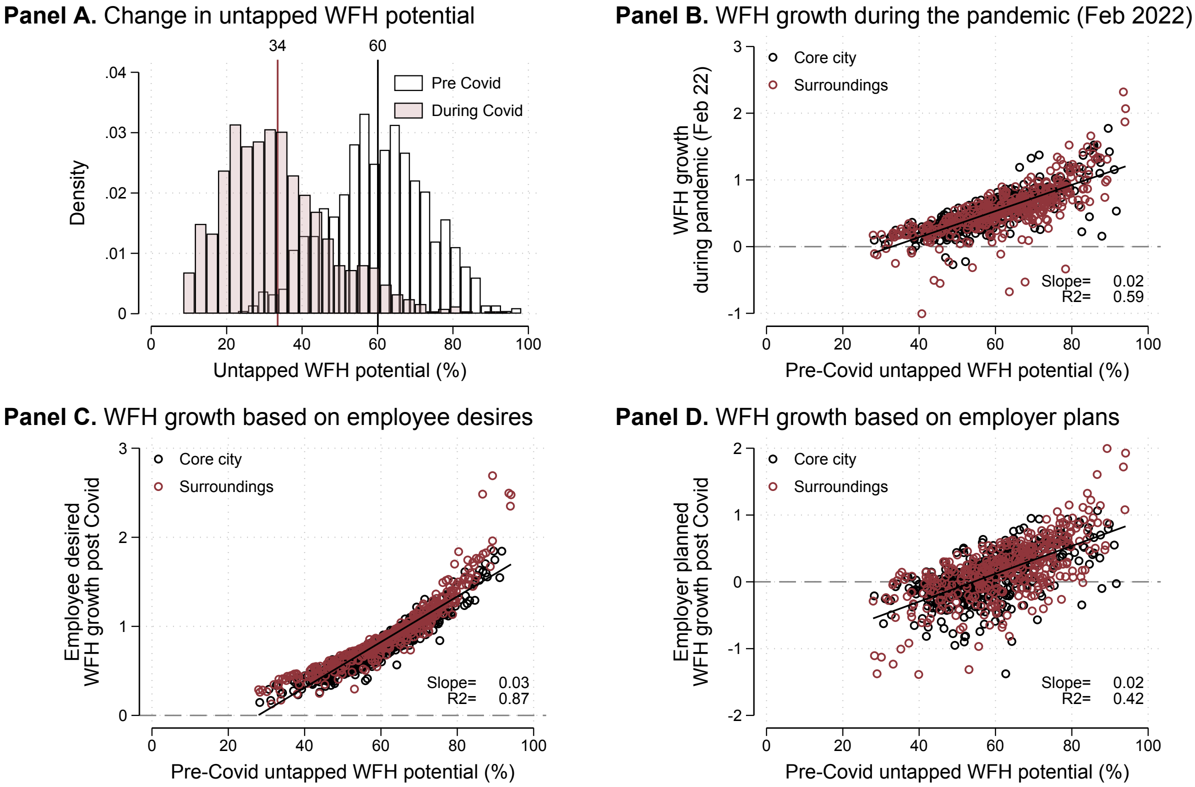
First, we propose a measure of "untapped WFH potential", defined as the share of employees with a teleworkable job who *did not* work from home before the pandemic (Alipour et al., 2022). Importantly, WFH is measured at the place of residence (rather than the place of work). The idea is to approximate the local scope to *expand* WFH after the pandemic outbreak relative to occupation-related feasibility. Since untapped WFH potential is measured pre Covid it is unaffected by other sources of spending disruptions. Using this measure instead of WFH uptake during the pandemic as our key explanatory variable thus lessens some endogeneity concerns. Panel A of Figure 3 reports the distribution of untapped WFH potential across postcodes before the pandemic and in February 2022. The distribution significantly shifted leftward as firms and employees went remote to reduce work-related contacts, exploiting their WFH potential. Panel B demonstrates that untapped WFH potential performs remarkably well in predicting observed WFH growth in February 2022 relative to pre-Covid levels. The result is similar when estimated for each metro area separately (see Appendix Figure A.15). Overall, the measure alone explains about 60 percent of the variation in WFH uptake during the pandemic. Panels C and D show that the strong relationship persists when using WFH growth rates based on employee desires and employer plans for the post-pandemic future. The results bolster the case that pre-Covid untapped WFH potential is an informative measure for the local shifts to WFH during and beyond the pandemic.

One may still be concerned that untapped WFH potential is not completely orthogonal to other determinants of spending shifts. If, for instance, the measure is correlated with the local industry composition, then our estimates may pick up supply-side disruptions due to business closures rather than WFH effects. Differences in local population structure may also afflict our estimates if people react differently to the Covid shock, e.g., by adjusting the composition of their spending to varying degrees or because of differences in the propensity to shift from cash to card payment. In the aggregate, card payments in total consumer spending increased only moderately from 48 to 52 percent between 2019 and 2020. The same is true regarding the number of debit and credit cards issued and the number of POS terminals used by merchants for accepting card payments (see Appendix Figure A.16). Still, substitution rates may be heterogeneous and correlated with untapped WFH potential. Thus, our second step to alleviate remaining endogeneity concerns involves comprehensively controlling for supply-side and structural factors that may be correlated with both untapped WFH potential and time trends. Formally, we include a vector of time-invariant controls $\mathbf{X}$ interacted with monthly dummies in our modified DiD specification:

$$Spending_{ct} = \sum_{k \neq Feb\_2020} [\mu^k \mathbb{1}(k=t) \times untap\_WFH\_pot_c + \mathbb{1}(k=t) \times \mathbf{X}_c' \pi^k] + \alpha_c + \gamma_t + \varepsilon_{ct}, \tag{2}$$

where $untap\_WFH\_pot$ is standardized (mean zero and unitary standard deviation) pre-Covid untapped WFH potential and α_c, γ_t are postcode and month-year fixed effects. The vector $\mathbf{X}$ comprises measures of the local commercial structure and industry

Figure 3: Untapped WFH Potential and WFH Growth



Notes: Panel A reports histograms of untapped WFH potential pre-Covid and during Covid (February 2022) at the postcode level. Panels B–D show linear fits between WFH growth rates and pre-Covid untapped WFH potential after partialling out five metro area fixed effects. WFH growth is the share of employees working at least one day per week from home relative to pre-Covid levels using self-reported WFH during Covid (February 2022) in Panel B, self-reported WFH desires for the post-Covid future in Panel C, and employee-reported plans of their employers for the post-Covid future in Panel D. Data are from *infas360*.

composition (business density, 2019 consumption intensity, a dummy for the presence of a shopping center, as well as the share of businesses in retail, food & accommodation, arts & entertainment, other service activities, professional & technical activities, construction, and education respectively) and of the local population and settlement structure (population density, the share of addresses with residential use, the share of low-income households, the share of foreign residents, the share of married residents, as well as the share of residents under 15, between 15 and 29, and over 65, respectively). Thus, our estimates of interest $\hat{\mu}^k$ trace the differential time trend between high and low untapped WFH potential areas *clean* of trend differentials across any of the characteristics included in **X**. We again use February 2020 as the reference period and cluster standard errors at the postcode level.[7]

We start by presenting DiD coefficients conditional on time and postcode fixed effects only in Figure 4. [8] The outcome in Panel A is the log average daily spending over the whole week. The first feature that stands out is that pre-Covid coefficients appear close to zero and statistically insignificant, supporting the validity of our first identifying assumption that trends in outcomes across comparison groups evolve in parallel except through the Covid shock. With the beginning of the pandemic in March 2020, trends begin to diverge. Spending in postcodes with a higher untapped WFH increases significantly and remains different from zero thereafter. The estimates are driven by strong effects for all business days (Mondays to Fridays), whereas differences between postcodes turn mostly insignificant for a confined sample of spending on Saturdays shown in Panel B. These results are consistent with WFH as the driving mechanism, altering regional spending during regular working days by eliminating commutes and leaving weekend spending largely unaffected. We find no differences across business days, which is consistent with workplace mobility data from Google that indicates a general reduction in workplace mobility but no differential trends across business days (see Appendix Figure A.17).[9]

The full set of our DiD results is presented in Table 1. For better exposition, we group time indicators into six bins reflecting the different phases of the pandemic (and corresponding to the shaded areas in Figure 4); specifically, the pre-Covid period (reference group), the Spring 2020 lockdown, the open period in the summer 2020, the winter lockdown 2020/21, the open period in 2021/22, and the out-of-Covid transition after March 2022.

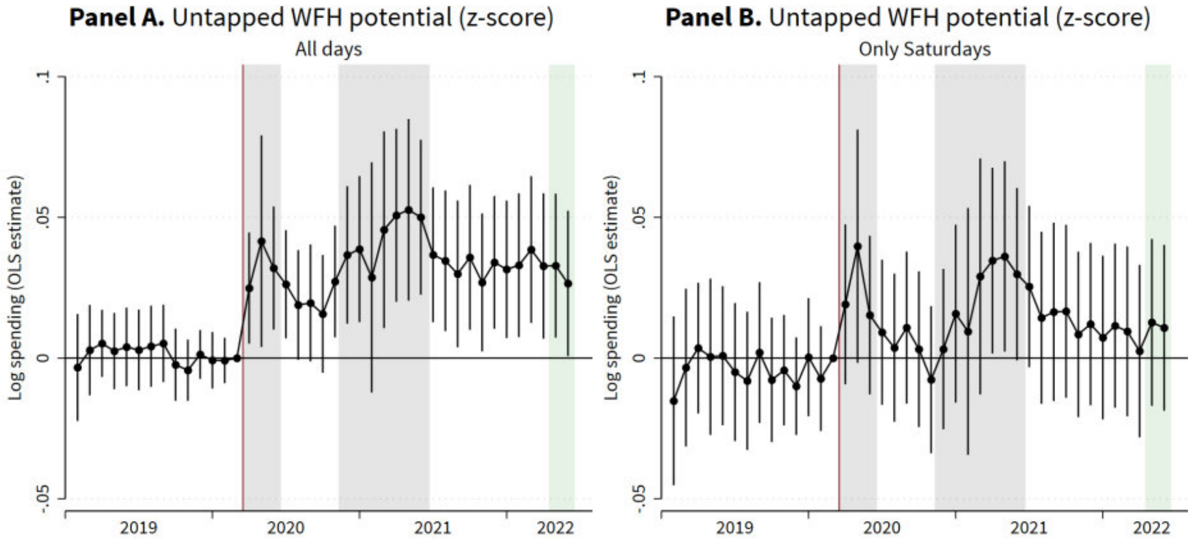
Columns (1) and (2) report the estimates conditional on postcode fixed effects and time fixed effects. The coefficients are significant in all periods for spending over the whole week and mostly insignificant for spending on Saturdays, mirroring the DiD plots in Figure 4. The remaining columns use business day (Monday-Friday) spending as the dependent variable to focus on consumption during working days. Column

[7]Alternative clustering of standard errors, e.g. at the postcode-month level or at city district categories to account for spatial spillovers, does not have a meaningful effect on the estimates.

[8]Appendix Figure A.21 show the descriptive line charts of spending by WFH growth and untapped WFH potential, analogously to Panel A of Figure 1.

[9]The heterogeneity of the WFH effect on consumer spending is most evident for the comparison of business days versus weekends, whereas the estimates hardly vary within these two groups. In other words, our results do not imply the existence of frequently used WFH days, which some observers might have assumed to be Mondays and/or Fridays.

Figure 4: DiD Results on the Association of Untapped WFH Potential and Log Spending



Notes: The figure plots DiD estimates β^k from separate regressions, in which the interaction terms are between monthly dummies and (standardized) untapped WFH potential. The dependent variable is average daily spending over all days in Panel A and average spending on Saturdays in Panel B. 95-percent confidence intervals are drawn using standard errors clustered at the postcode level. The vertical red line marks the outbreak of the Covid-19 pandemic between February and March 2020. The gray-shaded areas highlight "lockdown" periods, characterized by severe containment measures. The green-shaded area marks the period after March 2022, when nearly all restrictions have been lifted. Spending data comprise debit and credit card payments.

(3) reports the baseline results without further controls. The association between untapped WFH potential and spending is positive and significant in all periods. Column (4) controls for city-specific trends by including month fixed effects that are interacted with a metropolitan area indicator. The coefficients remain unchanged and significant, suggesting the absence of differential time trends across metropolitan areas. Column (5) includes commercial structure and industry composition controls, each separately interacted with a full set of month indicators. This attenuates the coefficients during lockdown periods and renders them statistically insignificant. The point estimates on open periods remain unchanged relative to Column (3). Column (6) replaces commercial controls×month fixed effects with interactions between population characteristics and time dummies. Finally, our most demanding specification in Column (7) absorbs all commercial and population controls, separately interacted with month fixed effects. The results remain essentially unchanged compared to Column (5). Once we account for other potential sources of spending disruptions, the impact of WFH becomes insignificant during lockdown periods and remains sizable and statistically different from zero in *non-lockdown periods*. On average, transaction volume increases by

2–3 percent for every standard deviation increase in untapped WFH potential during "open periods" and by 3 percent after restrictions are permanently lifted.

The lack of effects during periods with heavy containment measures and high infection risk is somewhat startling, given that social distancing provisions including WFH rates were particularly high during these months. One possible explanation is that—after holding local industry structure fixed—ubiquitous business closures during these periods preclude most of the potential relocation of offline spending. Instead of shifting regionally, consumption shifted from offline to online commerce.[10] Another possible explanation is related to the observation that the likelihood of job loss and short-time work is *negatively* correlated with the ability to work from home (Adams-Prassl et al., 2020; Alipour et al., 2021a). If during lockdowns, employees who cannot work remotely also stay at home because they are put on short-time work, then the spatial correlation between untapped WFH potential and spending may vanish. By contrast, the reopening of the economy leads to a shift of offline consumption into areas where employees keep working from home relative to areas in which employees leave the short-time work scheme.

Another potential concern might be that our estimates of the spatial spending shifts do not only capture the WFH effect, but part of the effect may stem from migration out of city centers to the suburbs and surrounding areas. This migration could be the result of increased WFH opportunities. Administrative population statistics from the metropolitan areas in our sample do not support this hypothesis. This mechanism may become more important in the long run, reinforcing the effects we document in this paper.

[10] As shown in Appendix Figure A.7, the share of online spending reached conspicuous spikes during lockdown periods.

Table 1: DiD Results on the Intention-to-Treat Effects of WFH on Log Spending

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Pre-Covid Untapped WFH Potential (z-score)							
× Lockdown Spring 2020	0.03**	0.03**	0.03**	0.03**	0.00	0.00	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
× Open Period Summer 2020	0.02**	0.01	0.02**	0.02**	0.02*	0.02*	0.02*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
× Lockdown Winter 2020/21	0.04***	0.03*	0.05***	0.05***	0.02	0.01	0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
× Open Period Summer/Winter 2021/22	0.03***	0.02	0.04***	0.03***	0.03***	0.03***	0.03***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
× Out-of-Covid Transition 2022	0.03**	0.02	0.03**	0.03**	0.03**	0.03**	0.03***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
R^2	0.87	0.87	0.87	0.87	0.90	0.89	0.90
Observations	33,191	33,113	33,190	33,190	33,190	33,190	33,190
Sample	All Days	Saturdays	Mo-Fr	Mo-Fr	Mo-Fr	Mo-Fr	Mo-Fr
Postcode FE	×	×	×	×	×	×	×
Month FE	×	×	×		×	×	×
Month FE × Metro Area FE				×			
Month FE × Commercial Structure					×		×
Month FE × Sociodemographic Structure						×	×

Notes: The table reports DiD estimates $\hat{\mu}^k$ based on Equation 2. Time dummies are grouped into six bins; specifically, the pre-Covid period (reference group), the Spring 2020 lockdown, the open period in the summer 2020, the winter lockdown 2020/21, the open period in 2021/22, and the out-of-Covid transition after March 2022. The dependent variable is the log average monthly offline spending. Baseline estimates for all days in the specification with postcode and month fixed effects are displayed in column (1). In column (2), the outcome is the log average spending on Saturdays. Column (3) shows the results for spending restricted to business days (Mondays through Fridays). Column (4) controls for month times metro area fixed effects. Column (5) controls for month fixed effects separately interacted with measures of the local commercial structure (business density, 2019 consumption intensity, a dummy for the presence of a shopping center, as well as the share of businesses in retail, food & accommodation, arts & entertainment, other service activities, professional & technical activities, construction, and education respectively). Column (6) controls for month fixed effects separately interacted with measures of local population and settlement structure (population density, the share of addresses with residential use, the share of low-income households, the share of foreign residents, the share of married residents, as well as the share of residents under 15, between 15 and 29, and over 65, respectively). Column (7) includes the full set of controls interacted with month fixed effects. Standard errors are clustered at the postcode level and reported in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

4. Discussion and Outlook

Our study provides evidence that the pandemic has induced fundamental changes to the micro-geography of work and consumption in major cities. Analyzing detailed postcode-level data on offline consumer spending, we find spatial spending shifts from previously consumption-intensive urban centers towards less spending-intensive and more residential areas. We establish a causal relationship between the altered geography of work and consumer spending: A standard deviation increase in pre-Covid untapped WFH potential increases local offline spending by 2-3 percent after the end of pandemic restrictions. The effect is driven by spending during business days, rather than on Saturdays, and is only significant outside of lockdowns and once Covid restrictions are permanently lifted.

While our estimated consumption decline in city centers is roughly in line with the back-of-the-envelope calculations by Barrero et al. (2021b) of spending declines of 13 and 4.6 percent for Manhattan and San Francisco, our analysis is the first to provide a causal and micro-geographic estimate of such declines. Similar micro-geographical patterns have also been shown for the real estate market, with real estate prices declining most in city centers (Liu and Su, 2021; Bergeaud et al., 2021; Kwon et al., 2022).

What do our results imply for the future? WFH will most likely persist. Our survey data for the five metropolitan areas suggest that 30 percent of employees wish to work at least one day per week from home, up from 14 percent pre-Covid (see Appendix Figure A.18). The result regarding employee desires fits very well with the finding that employees highly value the option to WFH (Mas and Pallais, 2017). However, employer plans diverge from employee desires, which has also been documented by previous research (Aksoy et al., 2022). Averaging employee desires and employer plans in our sample yields an expected post-pandemic WFH rate of about 24 percent. This value matches Germany's actual WFH rate in February 2022 as well as WFH rates elicited in a nationally representative firm survey in April, August, and November 2022 (ifo Institute for Economic Research, 2022a,b,c). Both actual WFH rates in Germany and workplace mobility trends by Google indicate a high persistence of WFH. The WFH rate jumped from 5 percent pre-Covid to more than a quarter of employees, maintaining high levels throughout and beyond the crisis, and has been converging to the current level of roughly 25 percent. Similarly, workplace commutes have been stable at around 80 percent of pre-crisis levels since early 2022 (see Appendix Figure A.17 and Figure A.19). In combination, this underscores the magnitude and persistence of the WFH shock on labor markets. It is hence reasonable to assume that the high WFH uptake is stabilizing and that its effects on the micro-geography of consumption in cities can be cautiously extrapolated to the post-Covid future.

WFH causally contributes to the relocation of spending away from city centers. City suburbs and more outlying areas typically exhibit a higher pre-Covid untapped WFH potential, giving rise to a tentative "donut" (see Appendix Figure A.20 for the regional distribution of untapped WFH potential and WFH growth in February 2022 relative to pre-Covid). On average, moving from the 25th to the 75th percentile in the distribution of untapped WFH potential is associated with a 26 percent increase in distance to the city center ($p < 0.01$) and, based on our DiD estimates, causes a 15 percent increase in local spending.

Overall, the altered micro-geography of work and consumption has important implications for major cities and might reshape them in the future. While suburbs benefit and online consumption increases, city centers are faced with challenges, such as emptying offices and less frequented retail stores. Whether local businesses survive, how much traffic there is, and how buildings are being used — all of that depends on how many people come to the city regularly. While the effects on consumption are already observable in the short-run, much of the effects will only realize in the long-run and thus are avenues for future research. Nevertheless, urban planners might consider creating more mixed-use areas and less restrictive zoning rules in the future, which better connect residential, office, and shopping areas. It remains up to future research to keep track of this development.

References

Adams-Prassl, A., Boneva, T., Golin, M., and Rauh, C. (2020). Inequality in the Impact of the Coronavirus Shock: Evidence from Real Time Surveys. *Journal of Public Economics*, 189:104245.

Aksoy, C. G., Barrero, J. M., Bloom, N., Davis, S. J., Dolls, M., and Zarate, P. (2022). Working From Home Around the World. *NBER Working Paper*, 30446:1–66.

Alcedo, J., Cavallo, A., Dwyer, B., Mishra, P., and Spilimbergo, A. (2022). E-Commerce During Covid: Stylized Facts from 47 Economies. *NBER Working Paper*, 29729:1–19.

Alipour, J.-V., Fadinger, H., and Schymik, J. (2021a). My Home is my Castle – The Benefits of Working From Home during a Pandemic Crisis. *Journal of Public Economics*, 196:104373.

Alipour, J.-V., Falck, O., and Schüller, S. (2022). Germany's Capacity to Work From Home. *European Economic Review*, forthcoming:1–36.

Alipour, J.-V., Langer, C., and O'Kane, L. (2021b). Is Working From Home Here to Stay? A Look at 35 Million Job Ads. *CESifo Forum*, 22(6):1–6.

Althoff, L., Eckert, F., Ganapati, S., and Walsh, C. (2022). The Geography of Remote Work. *Regional Science and Urban Economics*, 93:103770.

Bamieh, O. and Ziegler, L. (2022). Are Remote Work Options the new Standard? Evidence from Vacancy Postings During the COVID-19 Crisis. *Labour Economics*, 76:102179.

Barrero, J. M., Bloom, N., and Davis, S. J. (2021a). Let me Work From Home or I Will Find Another Job. Mimeo:1–8.

Barrero, J. M., Bloom, N., and Davis, S. J. (2021b). Why Working From Home Will Stick. *NBER Working Paper*, 28731:1–62.

Bergeaud, A., Garcia, T., Eyméoud, J.-B., and Henricot, D. (2021). Working From Home and Corporate Real Estate. *SSRN Working Paper*, 3973122:1–27.

Bloom, N., Han, R., and Liang, J. (2022). How Hybrid Working From Home Works Out. *NBER Working Paper*, 30292:1–47.

Chen, H., Qian, W., and Wen, Q. (2021). The Impact of the COVID-19 Pandemic on Consumption: Learning from High Frequency Transaction Data. *AEA Papers and Proceedings*, 111:1–51.

Chetty, R., Friedman, J., Hendren, N., Stepner, M., and Team, T. O. I. (2020a). The Economic Impacts of COVID-19: Evidence from a New Public Database Built Using Private Sector Data. *NBER Working Paper*, 27431:1–108.

Chetty, R., Friedman, J. N., Hendren, N., and Stepner, M. (2020b). Real-Time Economics: A New Platform to Track the Impacts of COVID-19 on People, Businesses, and Communities Using Private Sector Data. *NBER Working Paper*, 27431:1–26.

De Fraja, G., Matheson, J., Mizen, P., Rockey, J., and Taneja, S. (2022). Remote Working and the new Geography of Local Service Spending. *CEPR Discussion Paper*, 17431:1–38.

De Fraja, G., Matheson, J., Mizen, P., Rockey, J. C., Taneja, S., and Thwaites, G. (2021). Covid Reallocation of Spending: The Effect of Remote Working on the Retail and Hospitality Sector. *SSRN Working Paper*, 3982122:1–48.

ECB (2020). Payment Statistics.

ECB (2021). Payment Statistics.

Florida, R., Rodríguez-Pose, A., and Storper, M. (2021). Cities in a Post-COVID World. *Urban Studies*, 0(0):1–23.

Glaeser, E. and Cutler, D. (2021). *Survival of the City: The Future of Urban Life in an Age of Isolation*. Penguin Press.

Gokan, T., Kichko, S., Matheson, J., and Thisse, J.-F. (2022). How the Rise of Teleworking Will Reshape Labor Markets and Cities. *CESifo Working Paper*, 9952:1–52.

Google (2022). Google Covid-19 Community Mobility Report. *https://www.google.com/covid19/mobility/ [last accessed 10 December 2022].*

Gupta, A., Mittal, V., and Van Nieuwerburgh, S. (2022). Work From Home and the Office Real Estate Apocalypse. *NBER Working Paper*, 30526:1–77.

Hystreet (2022). Pedestrian Frequency Data. *https://hystreet.com/ [last accessed 15 November 2022].*

ifo Institute for Economic Research (2022a). ifo Business Survey April 2022.

ifo Institute for Economic Research (2022b). ifo Business Survey August 2022.

ifo Institute for Economic Research (2022c). ifo Business Survey November 2022.

Kwon, E., Parkhomenko, A., and Delventhal, M. J. (2022). How do Cities Change When we Work From Home? *Journal of Urban Economics: Insights*, 127:1–20.

Liu, S. and Su, Y. (2021). The Impact of the COVID-19 Pandemic on the Demand for Density: Evidence from the U.S. Housing Market. *Economics Letters*, 207(110010):1–4.

Mas, A. and Pallais, A. (2017). Valuing Alternative Work Arrangements. *American Economic Review*, 107(12):3722–3759.

Ramani, A. and Bloom, N. (2021). The Donut Effect of Covid-19 on Cities. *NBER Working Paper*, 28876:1–36.

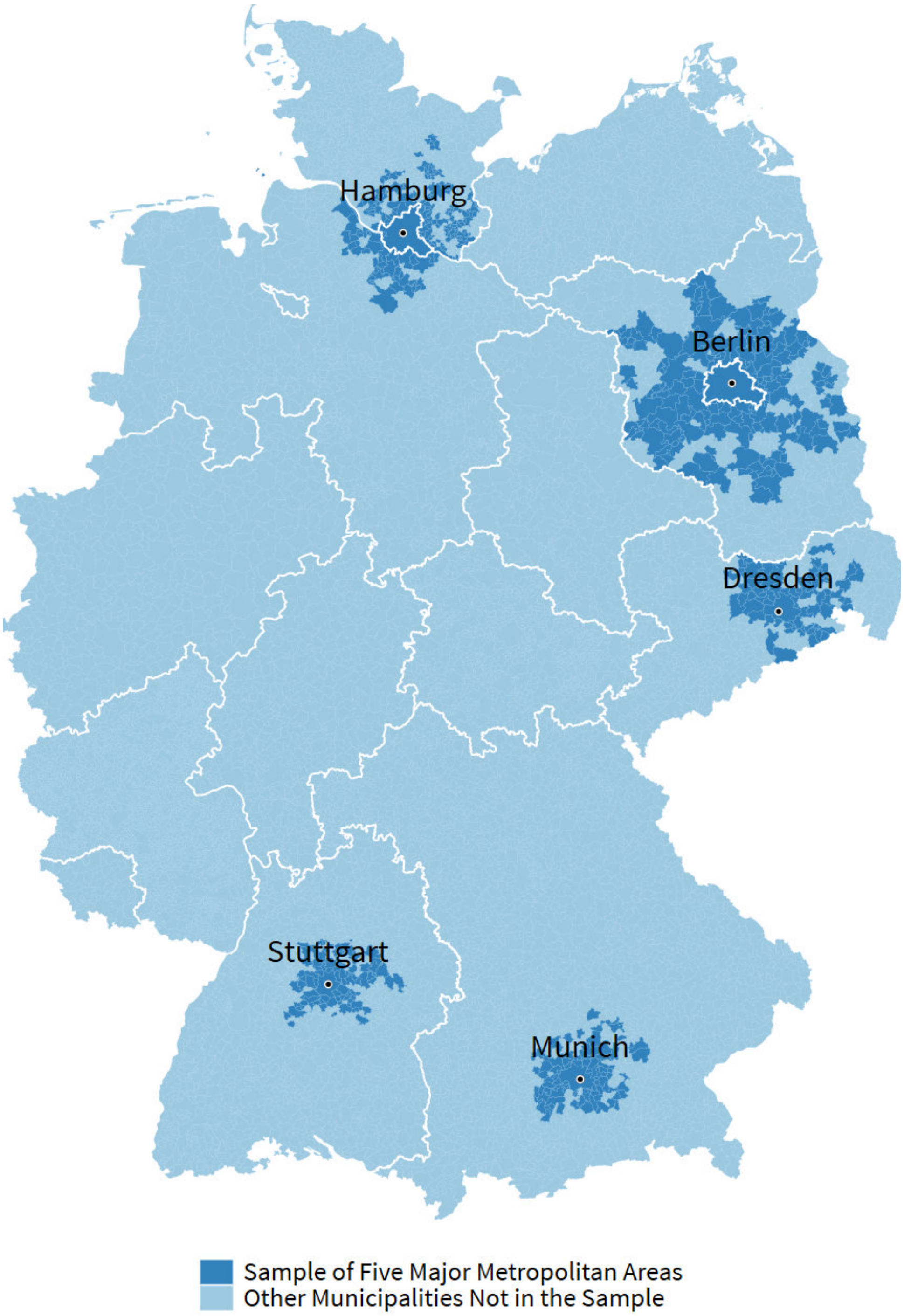
Redding, S. J. (2022). The Economics of Cities: From Theory to Data. *Journal of Economic Perspectives*, forthcoming:1–39.

Rosenthal, S. S., Strange, W. C., and Urrego, J. A. (2021). Are City Centers Losing their Appeal? Commercial Real Estate, Urban Spatial Structure, and COVID-19. *Journal of Urban Economics: Insights*, 103381:1–27.

Statista (2020). Payment Cards Market Shares Germany. *https://www.statista.com/statistics/972307/germany-payment-cards-share/ [last accessed 12 October 2022].*

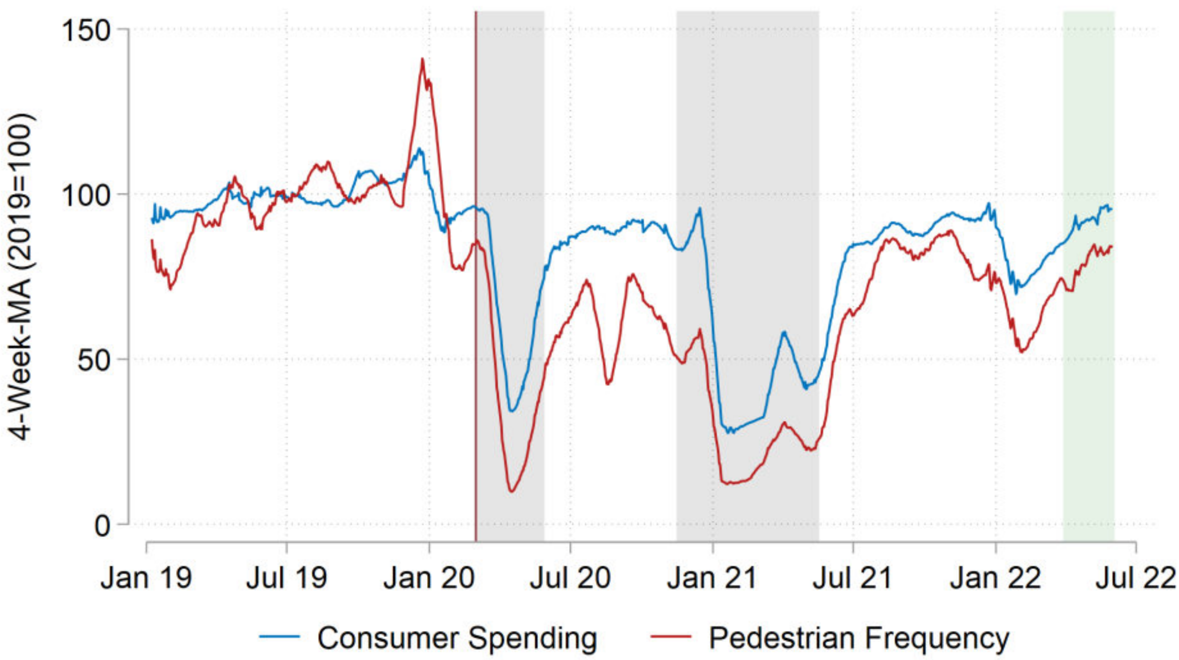
Appendix A. Figures

Figure A.1: Sample Illustration of Five Major German Metropolitan Areas



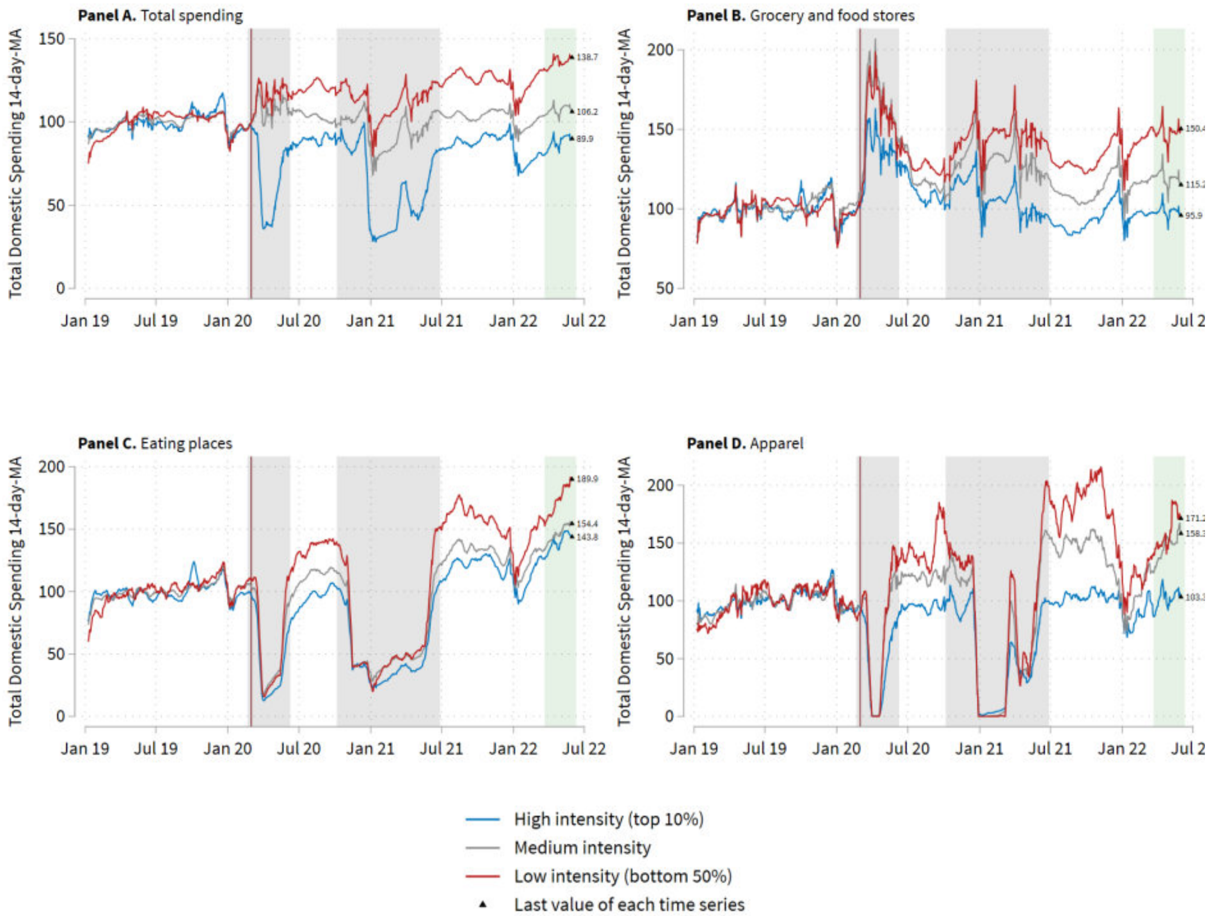
Notes: This map of Germany shows our sample of five major German cities and their surrounding areas: Berlin, Munich, Hamburg, Stuttgart, and Dresden. The municipalities with postcodes belonging to the sample are highlighted in dark blue. Light-blue shaded postcodes portrayed in the surrounding areas of the cities do not have measurable economic activity and are hence not included in the sample. The 16 German federal states are delineated by white border lines.

Figure A.2: Representativity of Consumer Spending Data: Comparison with Pedestrian Frequency 2019-2022



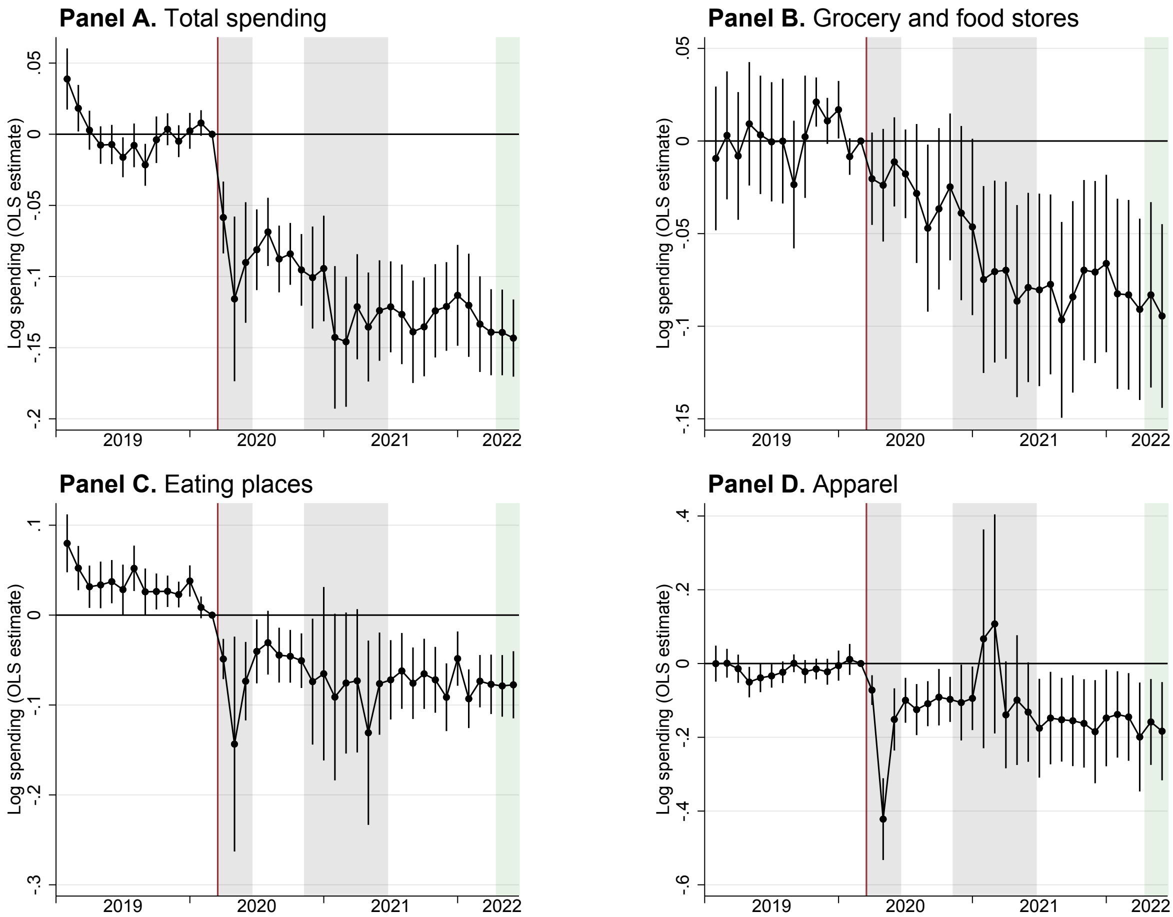
Notes: The figure shows the co-evolution of offline consumer spending (blue) and pedestrian frequency (red) in highly frequented postcodes. Time series show 4-week moving averages normalized by the 2019 average. The vertical red line marks the outbreak of the Covid-19 pandemic between February and March 2020. The gray-shaded areas highlight lockdown periods, characterized by closures of non-essential businesses and other severe containment measures. The green-shaded area marks the period after March 2022, when nearly all restrictions were lifted. The consumer spending data comprise debit and credit card payments. The pedestrian frequency data are provided by Hystreet (2022) who use laser scanners to track the number of pedestrians at measurement sites at prominent locations in cities.

Figure A.3: Spending Development by Consumption Intensity in Selected Sectors 2019-2022



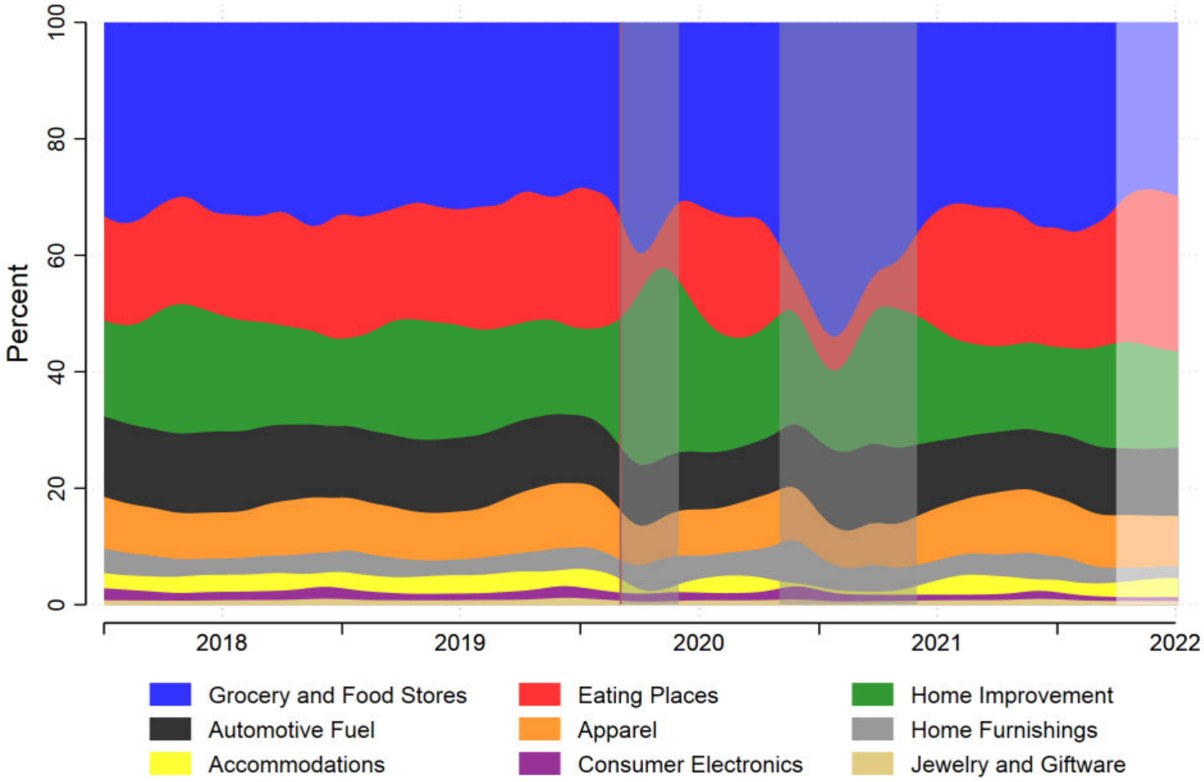
Notes: The figure shows the evolution of offline spending overall (Panel A), in grocery and food stores (Panel B), in eating places (Panel C), and in apparel stores (Panel D) by high, medium, and low 2019 consumption intensity. Time series show 14-day moving averages normalized by the 2019 average in each category. The vertical red line marks the outbreak of the Covid-19 pandemic between February and March 2020. The gray-shaded areas highlight lockdown periods, characterized by closures of non-essential businesses and other severe containment measures. The green-shaded area marks the period after March 2022, when nearly all restrictions were lifted. The consumer spending data comprise debit and credit card payments.

Figure A.4: DiD Results on the Association of Pre-Covid Consumption Intensity and Consumer Spending: Heterogeneity by Spending Categories



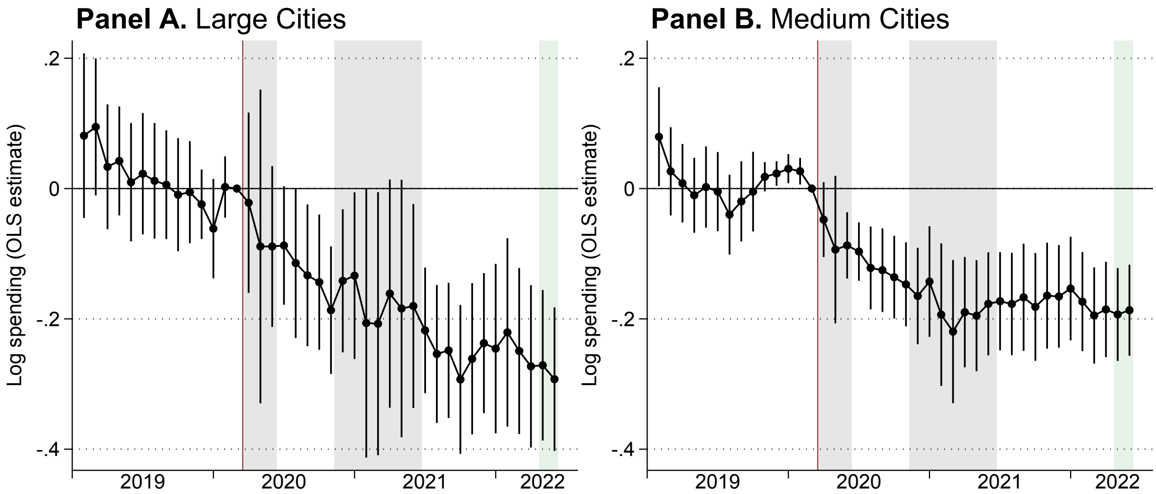
Notes: The figure plots the DiD estimates β^k on the interaction terms between standardized 2019 consumption intensity and monthly dummies (Equation 1). The dependent variables are average daily offline card spending overall (Panel A), spending in grocery and food stores (Panel B), spending in eating places (Panel C), and spending in apparel stores (Panel D). 95-percent confidence intervals are drawn using standard errors clustered at the postcode level. The vertical red line marks the outbreak of the Covid-19 pandemic between February and March 2020. The gray-shaded areas highlight lockdown periods, characterized by closures of non-essential businesses and other severe containment measures. The green-shaded area marks the period after March 2022, when nearly all restrictions were lifted. The consumer spending data comprise debit and credit card payments.

Figure A.5: Composition of Spending from 2018 to 2022



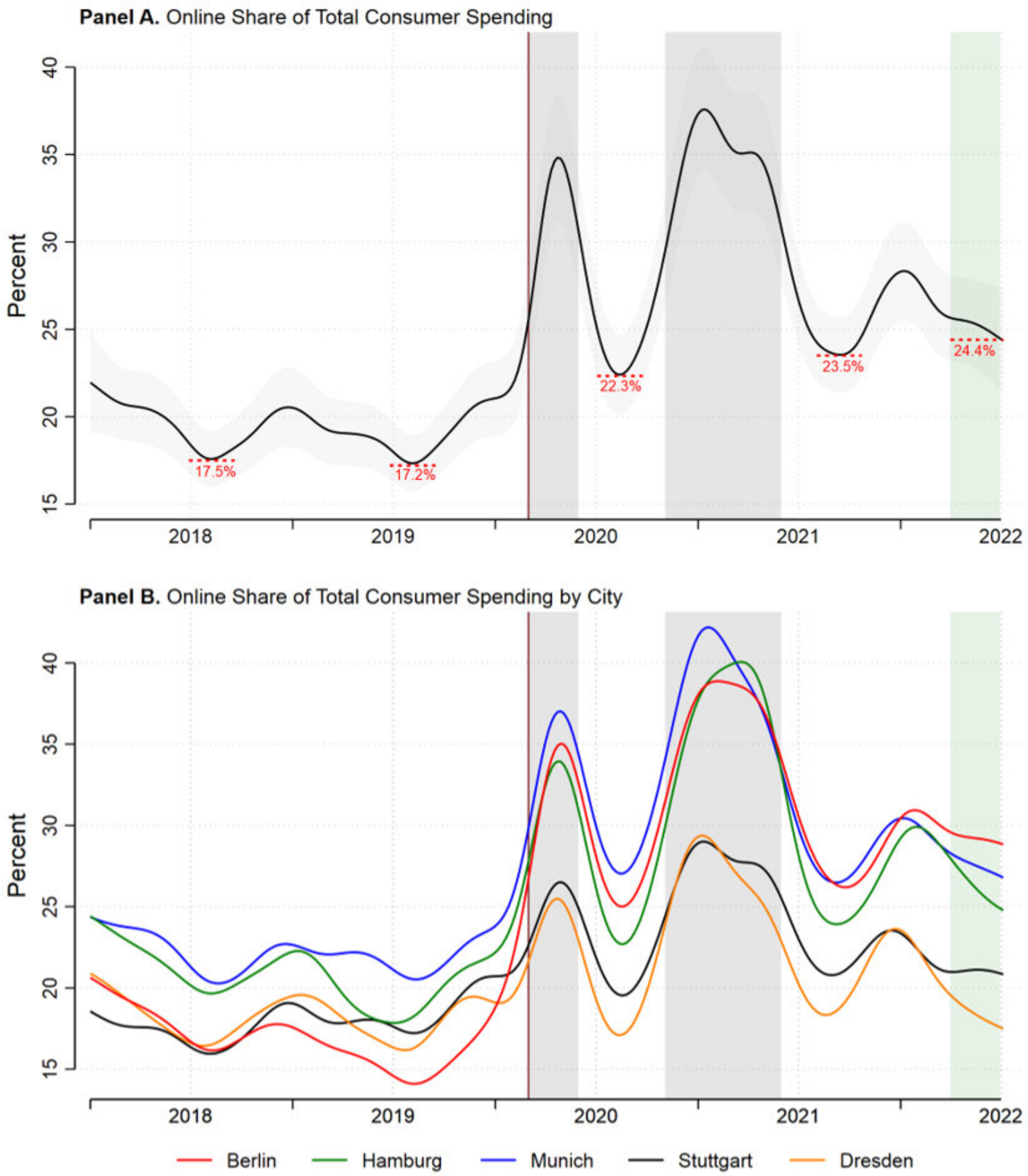
Notes: The stacked chart shows the composition of consumer spending from January 2018 through May 2022, depicting the shares of all spending categories and aggregates them up to up 100 percent throughout the period. The vertical red line marks the outbreak of the Covid-19 pandemic between February and March 2020. The vertical red line marks the outbreak of the Covid-19 pandemic between February and March 2020. The gray-shaded areas highlight lockdown periods, characterized by closures of non-essential businesses and other severe containment measures. The green-shaded area marks the period after March 2022, when nearly all restrictions were lifted. The data are based on Mastercard Spending Pulse, which comprises transaction information in the sample regions including online and offline spending.

Figure A.6: DiD Results on the Association of Pre-Covid Consumption Intensity and Consumer Spending: Heterogeneity by City Size



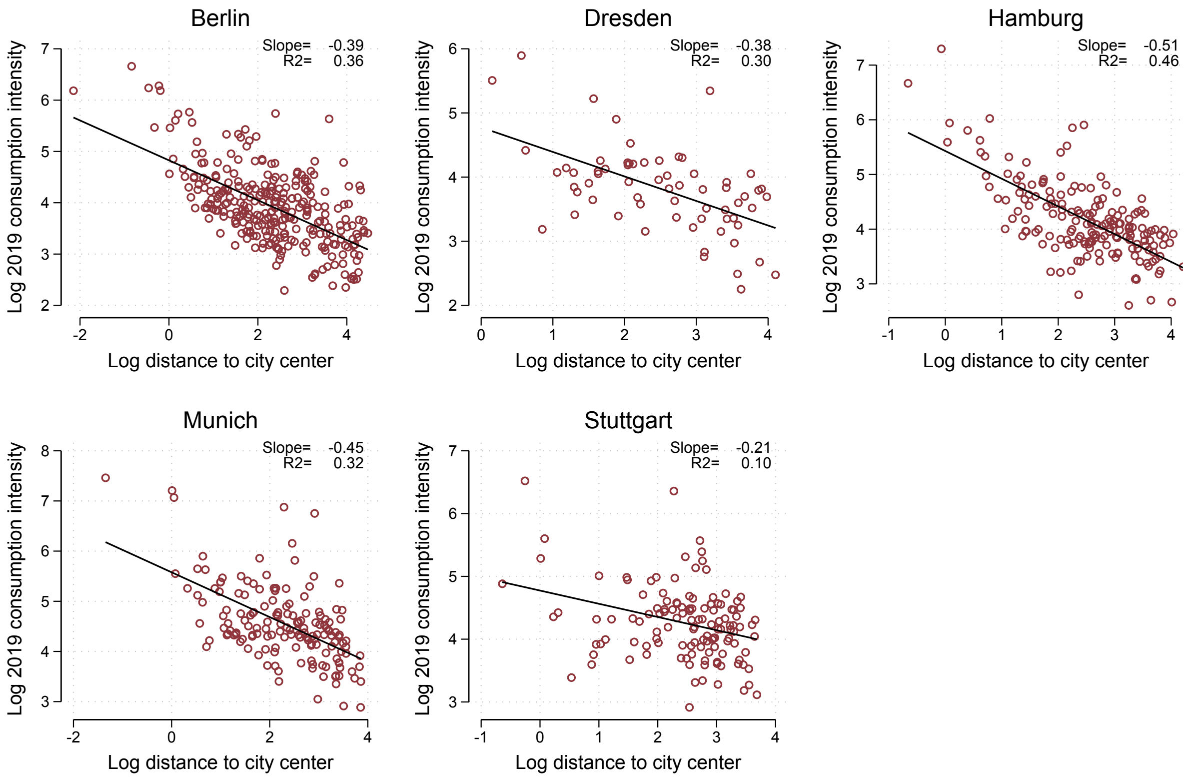
Notes: The figure plots the DiD estimates β^k on the interaction terms between standardized 2019 consumption intensity and monthly dummies (Equation 1). The dependent variables are average daily offline card spending overall in large cities (Panel A) and in medium cities (Panel B). Based on our sample, large cities are Berlin, Munich, and Hamburg, whereas medium cities are Stuttgart and Dresden. 95-percent confidence intervals are drawn using standard errors clustered at the postcode level. The vertical red line marks the outbreak of the Covid-19 pandemic between February and March 2020. The gray-shaded areas highlight lockdown periods, characterized by closures of non-essential businesses and other severe containment measures. The green-shaded area marks the period after March 2022, when nearly all restrictions were lifted. The consumer spending data comprise debit and credit card payments.

Figure A.7: Development of Online Payments Share of Total Consumer Spending, 2018-2022



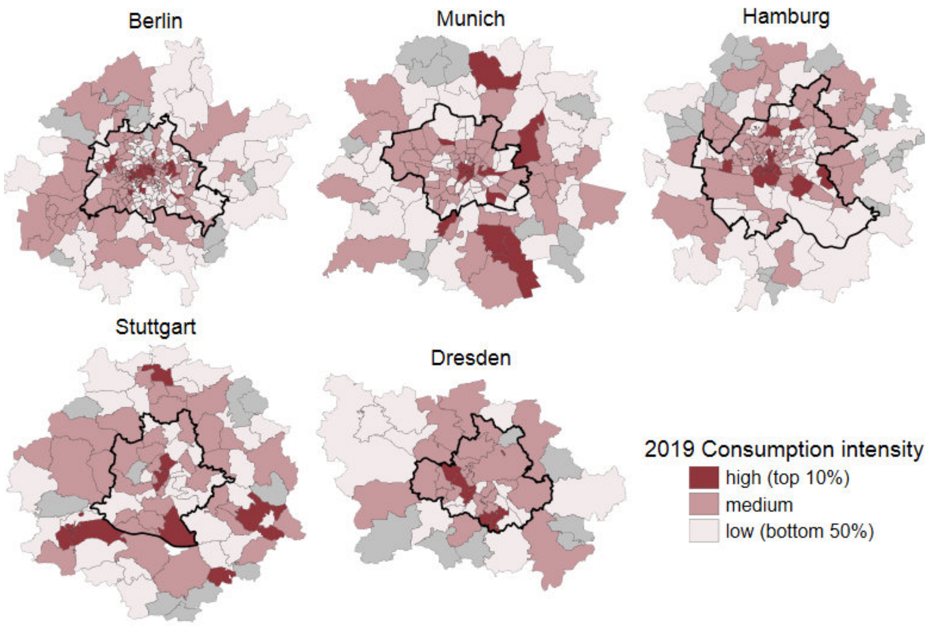
Notes: This figure shows smoothed daily online card payments as a share of total consumer spending from January 2018 through July 2022 (local polynomial smoothing). Panel A displays the weighted average of the five metropolitan areas including the 95 percent confidence intervals. The values under the dashed red horizontal lines report the minima for the summers of each year. Panel B displays the same time series for each of the metropolitan areas individually. The vertical red line marks the outbreak of the Covid-19 pandemic between February and March 2020. The gray-shaded areas highlight lockdown periods, characterized by closures of non-essential businesses and other severe containment measures. The green-shaded area marks the period after March 2022, when nearly all restrictions were lifted. The spending data are based on anonymized and aggregated transactions via cash, debit, and credit cards.

Figure A.8: Log Distance to the City Center and Log 2019 Consumption Intensity by Metro Area



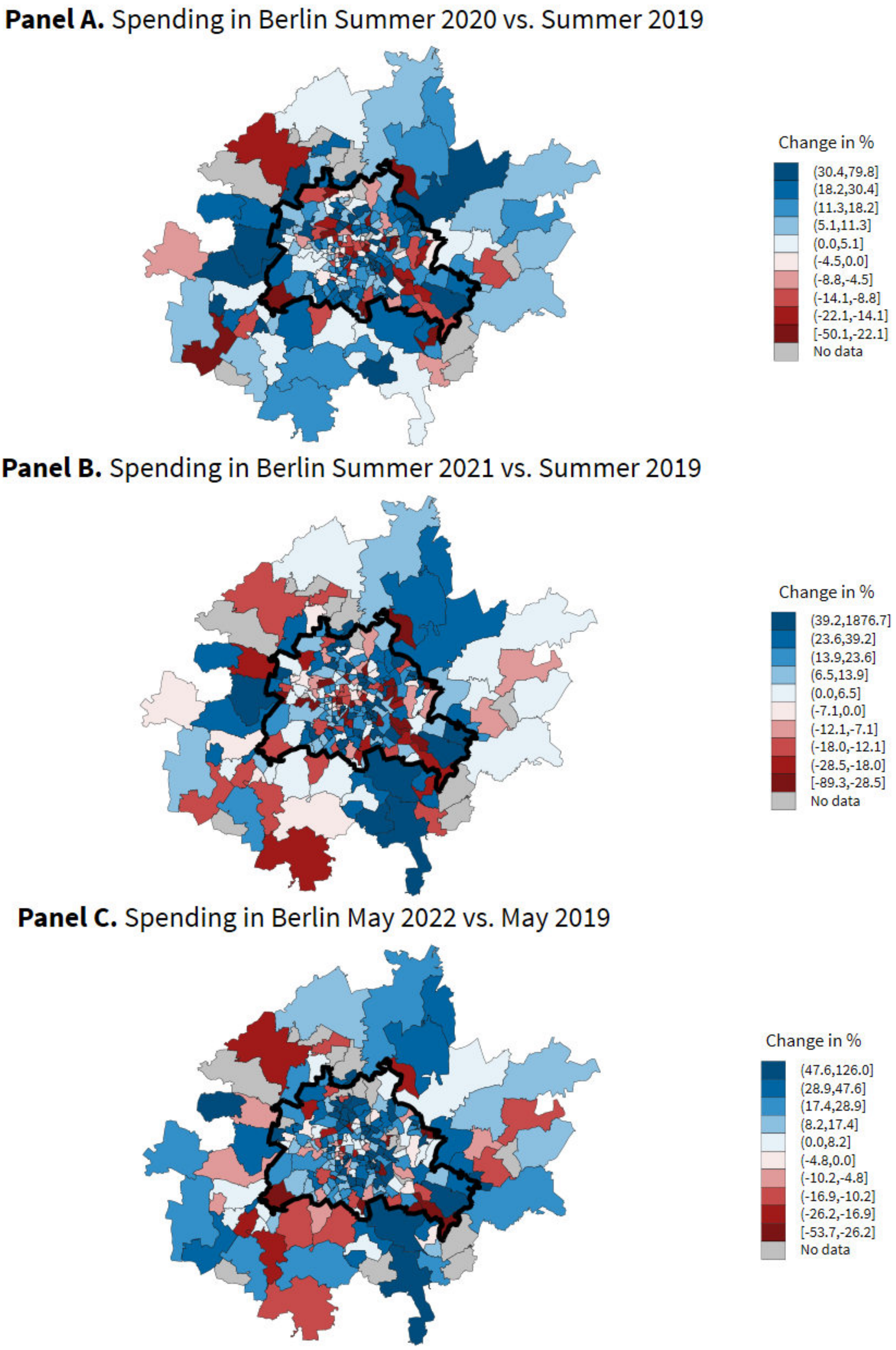
Notes: The figure plots the linear fit between log 2019 consumption intensity and log distance to the city center at the postcode level by metro area. Using heteroskedasticity-robust standard errors, all slopes are statistically different from zero at the one percent level. The consumer spending data comprise debit and credit card payments from *Mastercard* and the area characteristics data are provided by *infas360*.

Figure A.9: Spatial Distribution of 2019 Consumption Intensity



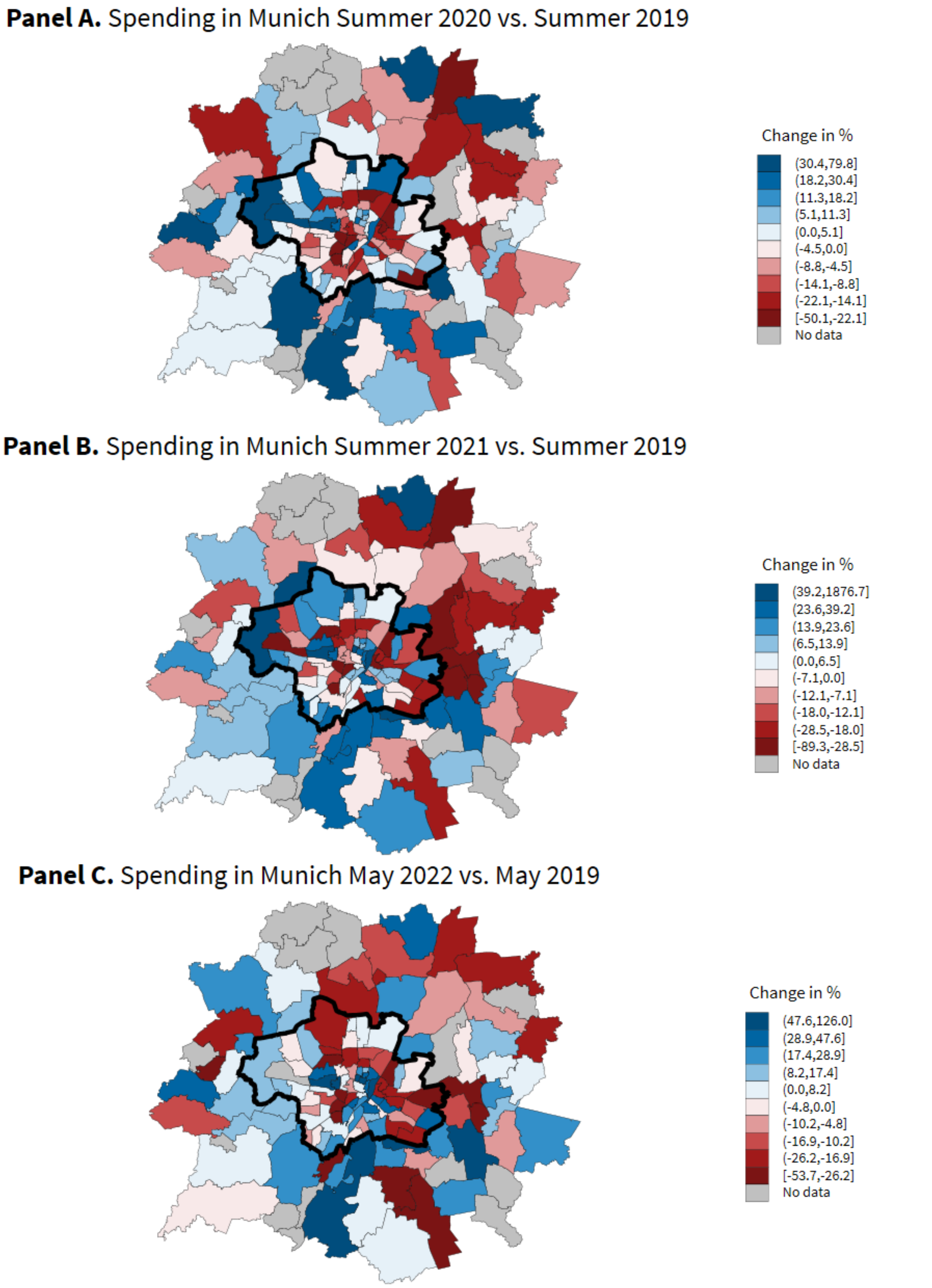
Notes: The figure displays the spatial distribution of 2019 consumption intensity at the postcode-level in the five sample cities and their surrounding areas. The black line marks the border between the city of Dresden and the surrounding municipalities. The classification distinguishes between high-consumption-intensity areas in dark red (top 10 percent of pre-pandemic spending), medium-consumption-intensity areas in light red, and low-consumption-intensity areas (bottom 50 percent of pre-pandemic spending) in very bright red. The consumer spending data comprise debit and credit card payments.

Figure A.10: Spatial Changes in Offline Consumer Spending in the Berlin Metropolitan Area



Notes: This figure shows changes in total offline spending by postcode in the metropolitan area of Berlin. The black line marks the border between the city of Berlin and the surrounding municipalities. Panel A displays the changes in consumer spending in June-September 2020, Panel B shows the spending development in June-September 2021, and Panel C the most recent spending changes from May 2022 – all compared with the respective pre-pandemic period in 2019. The consumer spending data comprise debit and credit card payments.

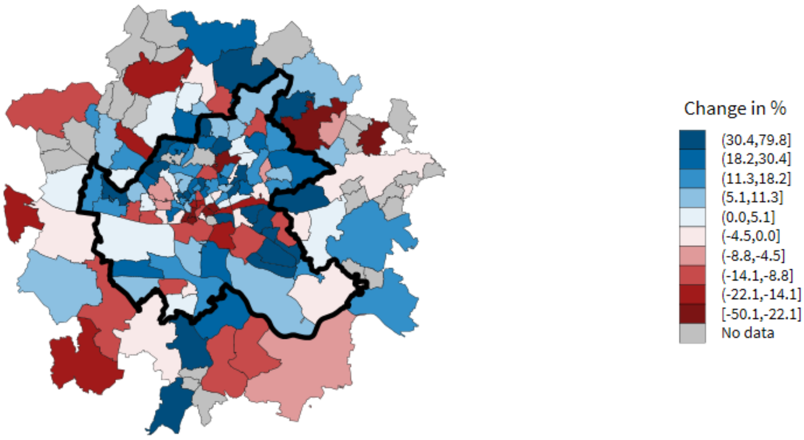
Figure A.11: Spatial Changes in Offline Consumer Spending in the Munich Metropolitan Area



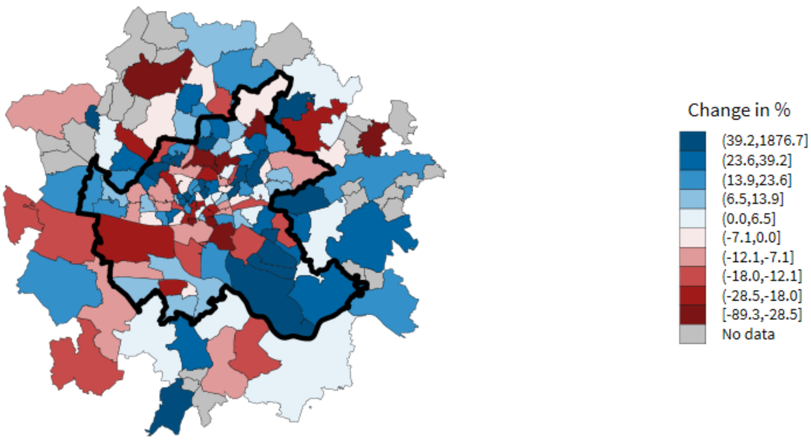
Notes: This figure shows changes in total offline spending by postcode in the metropolitan area of Munich. The black line marks the border between the city of Munich and the surrounding municipalities. Panel A displays the changes in consumer spending in June-September 2020, Panel B shows the spending development in June-September 2021, and Panel C the most recent spending changes from May 2022 – all compared with the respective pre-pandemic period in 2019. The consumer spending data comprise debit and credit card payments.

Figure A.12: Spatial Changes in Offline Consumer Spending in the Hamburg Metropolitan Area

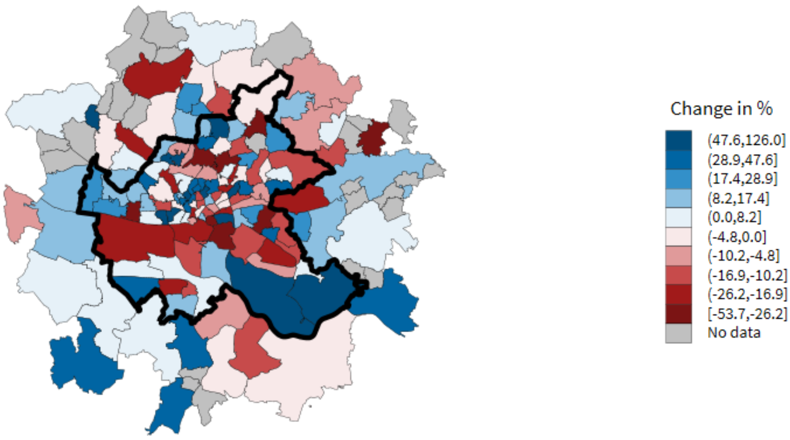
Panel A. Spending in Hamburg Summer 2020 vs. Summer 2019



Panel B. Spending in Hamburg Summer 2021 vs. Summer 2019

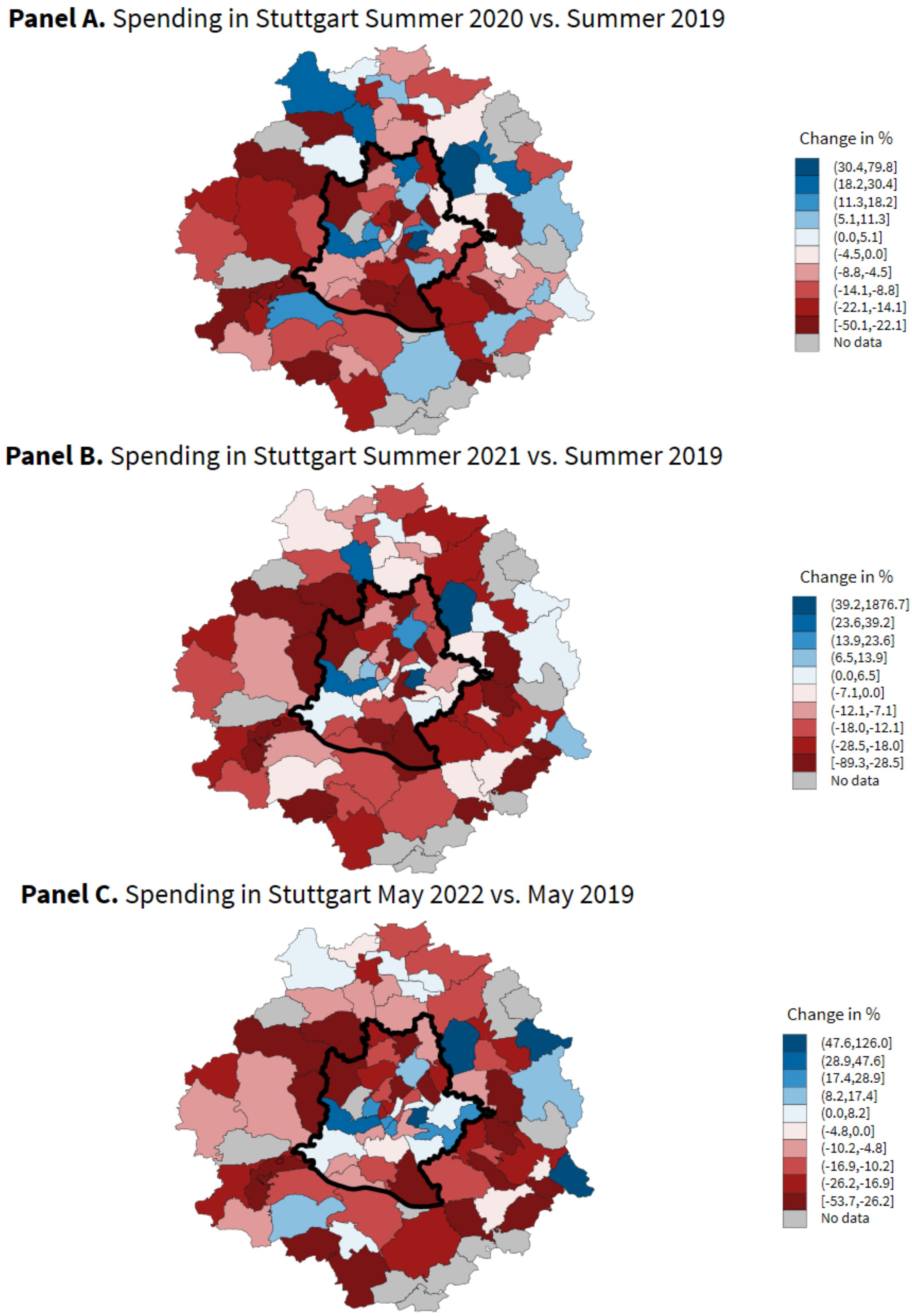


Panel C. Spending in Hamburg May 2022 vs. May 2019



Notes: This figure shows changes in total offline spending by postcode in the metropolitan area of Hamburg. The black line marks the border between the city of Hamburg and the surrounding municipalities. Panel A displays the changes in consumer spending in June-September 2020, Panel B shows the spending development in June-September 2021, and Panel C the most recent spending changes from May 2022 – all compared with the respective pre-pandemic period in 2019. The consumer spending data comprise debit and credit card payments.

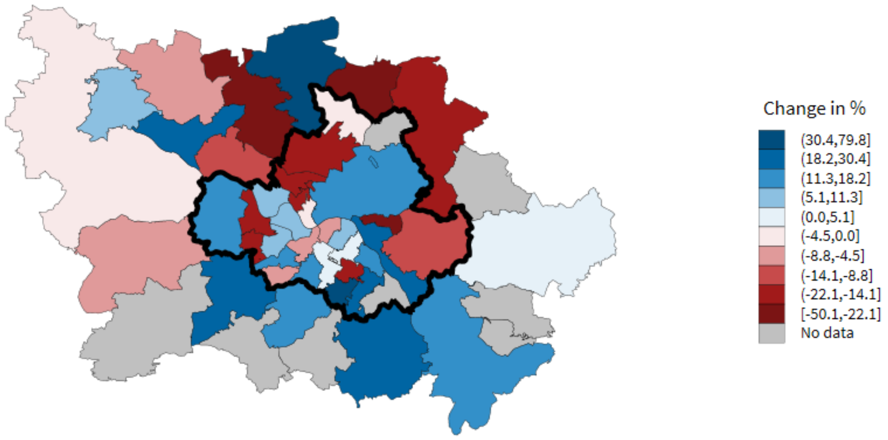
Figure A.13: Spatial Changes in Offline Consumer Spending in the Stuttgart Metropolitan Area



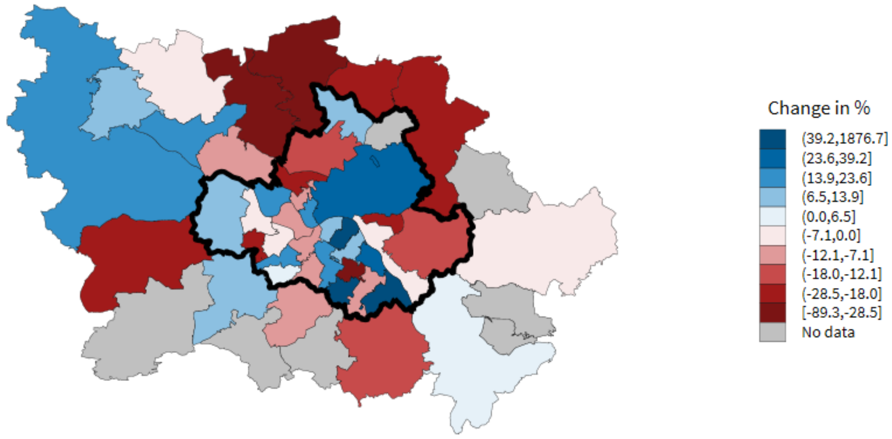
Notes: This figure shows changes in total offline spending by postcode in the metropolitan area of Stuttgart. The black line marks the border between the city of Stuttgart and the surrounding municipalities. Panel A displays the changes in consumer spending in June-September 2020, Panel B shows the spending development in June-September 2021, and Panel C the most recent spending changes from May 2022 – all compared with the respective pre-pandemic period in 2019. The consumer spending data comprise debit and credit card payments.

Figure A.14: Spatial Changes in Offline Consumer Spending in the Dresden Metropolitan Area

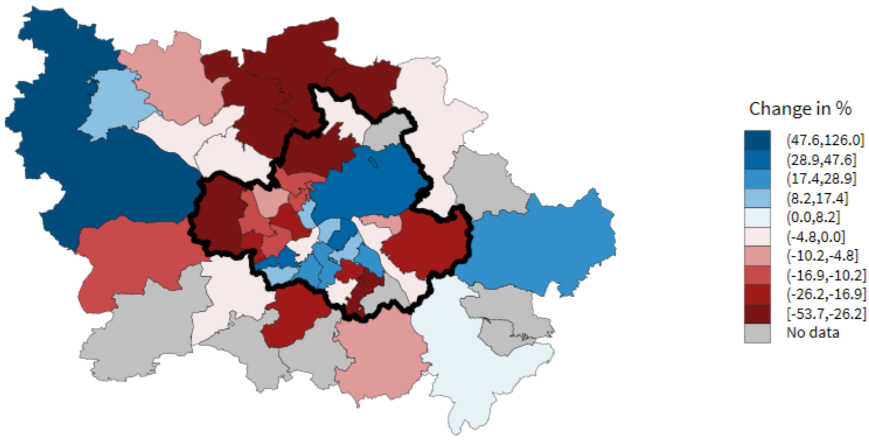
Panel A. Spending in Dresden Summer 2020 vs. Summer 2019



Panel B. Spending in Dresden Summer 2021 vs. Summer 2019

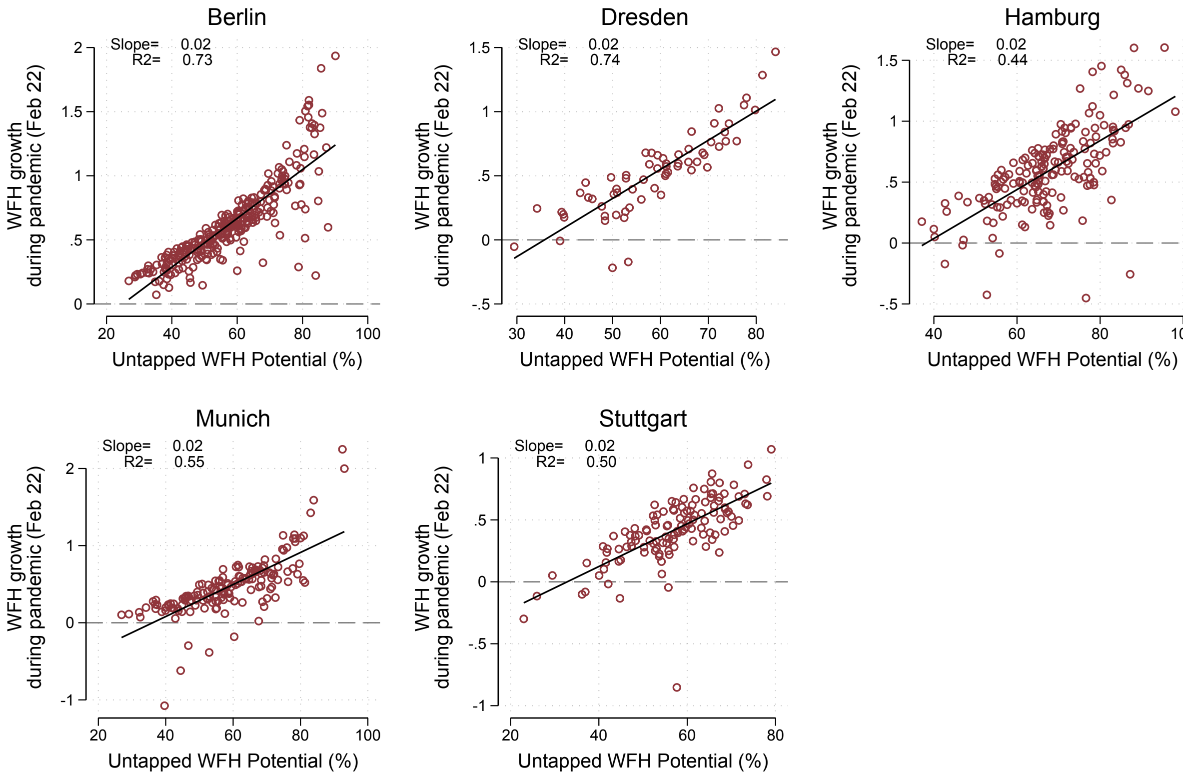


Panel C. Spending in Dresden May 2022 vs. May 2019



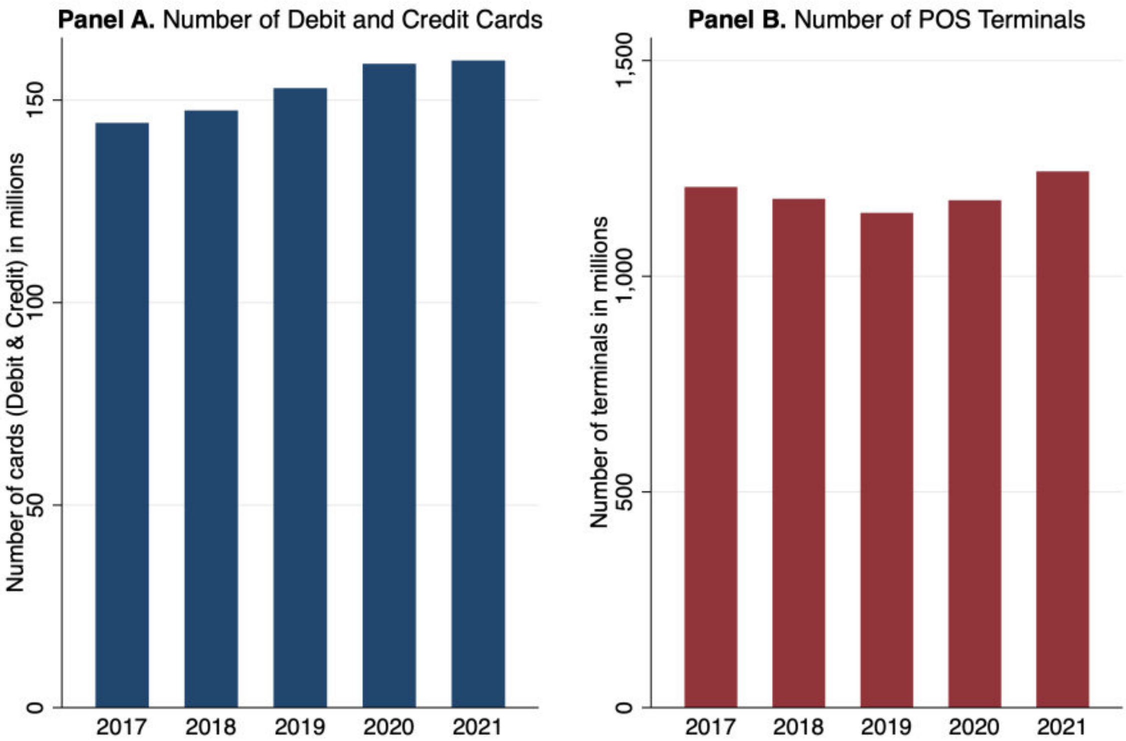
Notes: This figure shows changes in total offline spending by postcode in the metropolitan area of Dresden. The black line marks the border between the city of Dresden and the surrounding municipalities. Panel A displays the changes in consumer spending in June-September 2020, Panel B shows the spending development in June-September 2021, and Panel C the most recent spending changes from May 2022 – all compared with the respective pre-pandemic period in 2019. The consumer spending data comprise debit and credit card payments.

Figure A.15: Untapped WFH Potential and WFH Growth by Metro Area



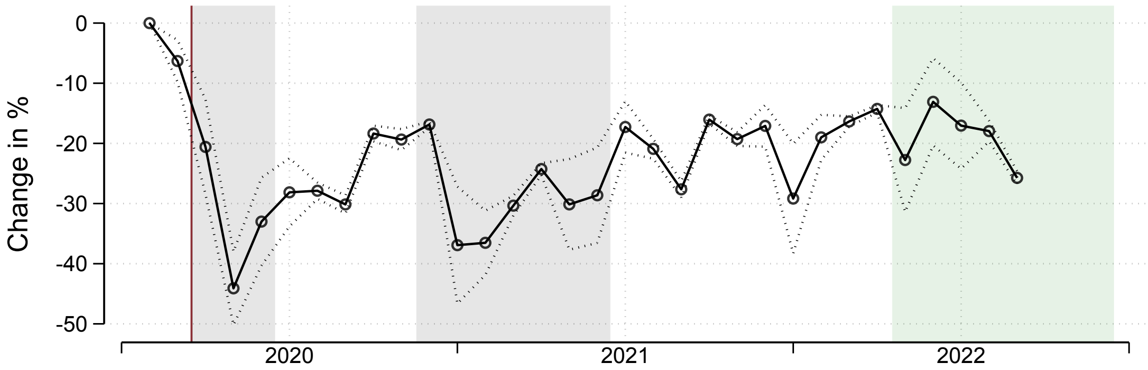
Notes: The figure plots the linear fit between local WFH growth during the pandemic (February 2020) and pre-Covid untapped WFH at the postcode level by metro area. Using heteroskedasticity-robust standard errors, all slopes are statistically different from zero at the one percent level. An auxiliary F-test cannot reject the hypothesis that the slopes are jointly equal to each other (p =0.13). Data are from *infas360*.

Figure A.16: Development of the Number of Consumer Payment Cards and POS Terminals in Germany, 2017-2021



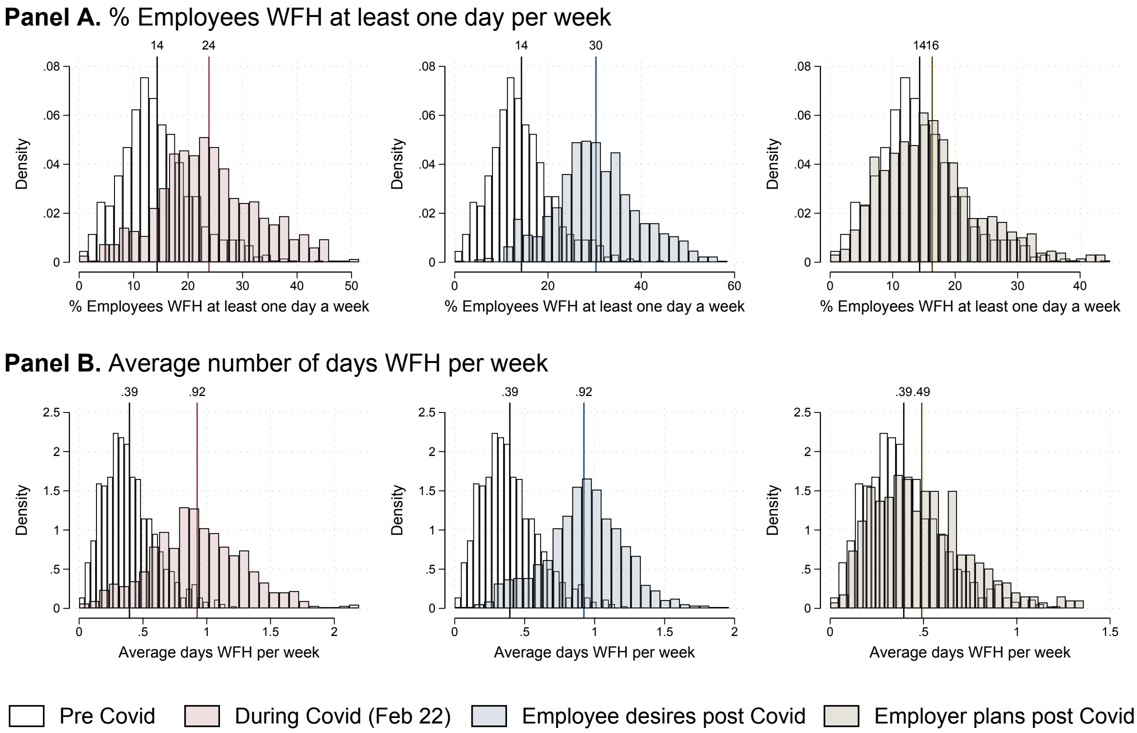
Notes: Panel A displays the development of the number of debit and credit cards issued in Germany from 2017 to 2021. Panel B portrays the number of POS terminals used by merchants for accepting card payments during the same period. The data stem from administrative payment statistics for Germany compiled by the European Central Bank (ECB, 2021).

Figure A.17: Google Workplace Mobility in Germany



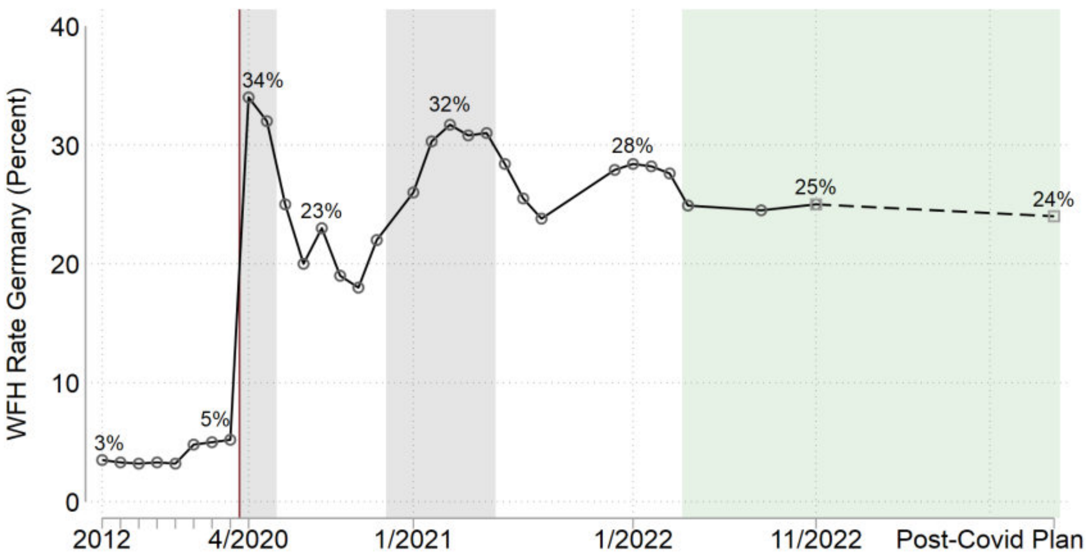
Notes: The figure plots Google's workplace mobility index for Germany. The index shows the average monthly percentage change in the number of workplace trips during weekdays (Mo-Fr) relative to January 2020 based on cellphone data. Dotted lines are the bootstrapped upper and lower bounds of the 95-percent confidence interval. The vertical red line marks the outbreak of the Covid-19 pandemic between February and March 2020. The gray-shaded areas highlight lockdown periods, characterized by closures of non-essential businesses and other severe containment measures. The green-shaded area marks the period after March 2022, when nearly all restrictions were lifted. The data are from Google (2022).

Figure A.18: WFH Before, During, and After the Covid-19 Pandemic



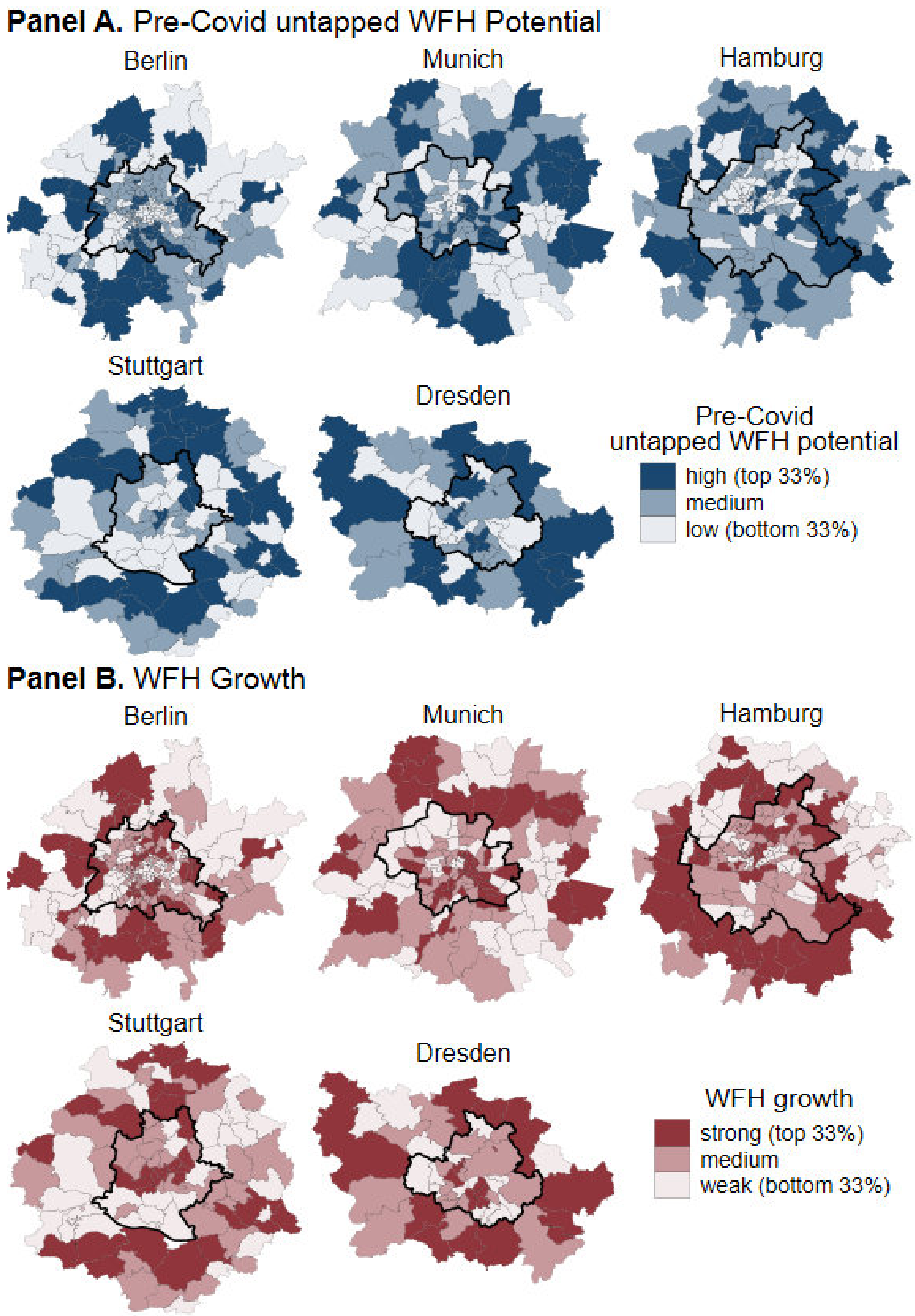
Notes: The figure plots histograms of the percentage of employees who WFH at least one day per week (Panel A) and of the average number of days of WFH per week (Panel B) pre-Covid, during Covid (column 1), according to self-reported desires for the post-Covid future (column 2), and according to employee-reported plans of their employers for the post-Covid future (column 3). Vertical lines highlight the mean of the distribution. The data are based on a representative survey conducted at the postcode level.

Figure A.19: WFH Rate in Germany over Time, 2012–Post-Covid Future



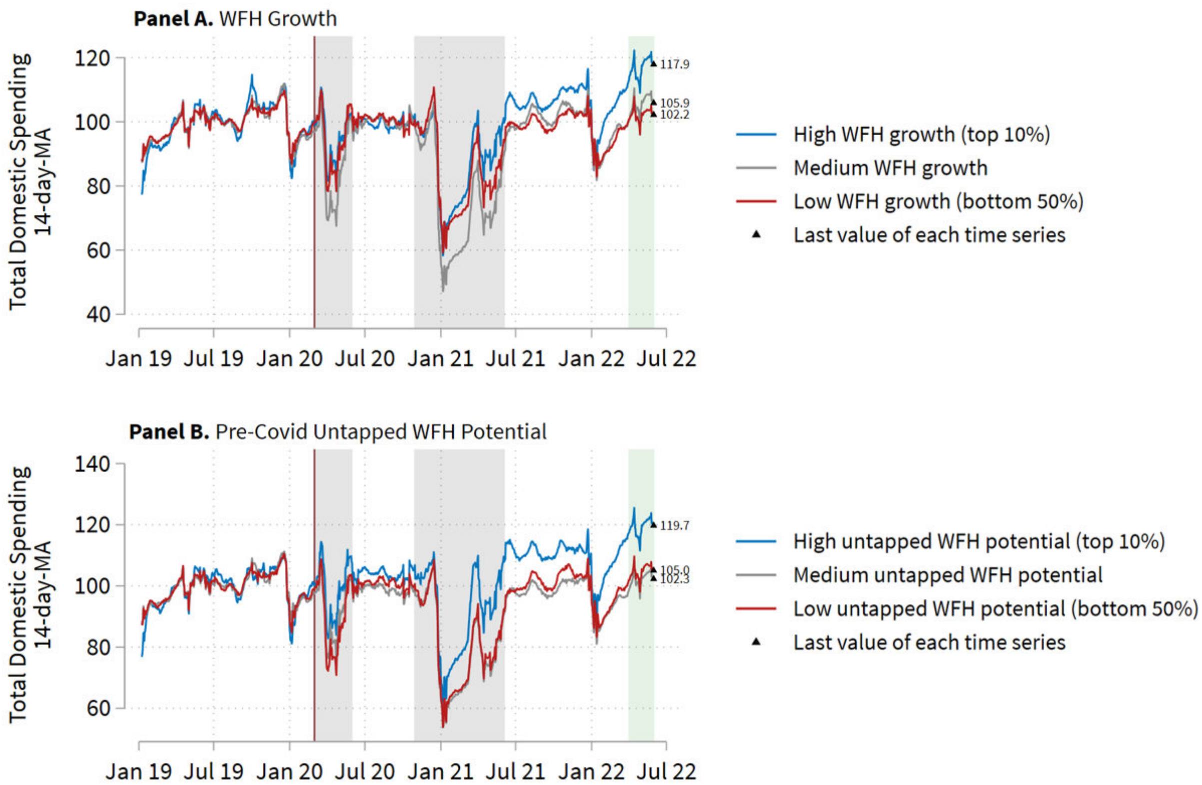
Notes: This time series chart shows the WFH rate in Germany since 2012, with the latest data point in November 2022 and including the post-Covid plans for the years ahead. The WFH rate is defined as the share of employees who WFH at least one day per week. The vertical red line marks the outbreak of the Covid-19 pandemic between February and March 2020. The gray-shaded areas highlight lockdown periods, characterized by closures of non-essential businesses and other severe containment measures. The green-shaded area marks the period after March 2022, when nearly all restrictions were lifted. The WFH data are based on Eurostat (2012-2019), infas360 and ifo Institute for Economic Research (2020-2022), and our representative survey for the post-pandemic WFH plans.

Figure A.20: Spatial Distribution of Pre-Covid Untapped WFH Potential and WFH Growth



Notes: The figure displays the spatial distribution of pre-Covid untapped WFH potential (Panel A) and WFH growth during the Covid-19 pandemic (February 2022) relative to pre-Covid levels (Panel B) for the five cities and their surroundings. Black solid lines delineate the core cities. Different shadings indicate whether postcodes belong to the top, medium, or bottom tercile of the city-specific distribution. The data are based on a representative survey conducted at the postcode level.

Figure A.21: Spending Development by WFH Growth and Untapped Potential 2019-2022



Notes: The figure shows the evolution of offline spending by high, medium, and low WFH growth (Panel A) and pre-Covid untapped WFH potential (Panel B). Time series show 14-day moving averages normalized by the 2019 average in each category. The vertical red line marks the outbreak of the Covid-19 pandemic between February and March 2020. The gray-shaded areas highlight lockdown periods, characterized by closures of non-essential businesses and other severe containment measures. The green-shaded area marks the period after March 2022, when nearly all restrictions were lifted. The consumer spending data comprise debit and credit card payments.

Appendix B. Tables

Table B.1: Summary Statistics

	Mean	SD	Min	Max
Panel A. Consumer Spending				
Total Spending (Index)	86.92	138.74	0.00	3376.07
2019 Consumption Intensity (Index)	90.62	132.54	9.50	1740.62
Panel B. Working From Home				
WFH Prior to Covid (Percent)	14.32	6.78	0.00	44.80
WFH Prior to Covid (Average Days per Week)	0.39	0.21	0.00	1.23
WFH Untapped Potential (Percent)	60.09	13.32	22.99	98.11
WFH During Covid (Percent)	23.84	9.24	0.00	51.38
WFH Growth (Percent)	83.84	76.35	-65.88	847.65
WFH Employee Desires After Covid (Percent)	30.28	9.28	0.00	58.48
WFH Employee Desires After Covid (Average Days per Week)	0.92	0.29	0.00	1.96
WFH Employer Plans After Covid (Percent)	16.33	7.93	0.00	44.04
WFH Employer Plans After Covid (Average Days per Week)	0.49	0.25	0.00	1.36
Panel C. Socioeconomic Indicators				
2019 Unemployment Rate	0.05	0.03	0.01	0.16
Purchasing Power (Per Capita)	25.53	5.90	15.39	51.69
Low-Income Households (Share)	0.22	0.18	0.00	0.88
Residents with Academic Degree (Share)	0.23	0.08	0.05	0.48
Living Space Per Household (sqm)	96.75	21.01	55.00	160.00
Average Rent (EUR/sqm)	9.51	2.64	5.25	18.47
Panel D. Population Structure				
Population	16291.22	7996.61	8	44608
Working Age Residents (Share)	0.66	0.05	0.51	0.88
Residents under 15 (Share)	0.14	0.02	0.02	0.27
Residents aged 65+ (Share)	0.20	0.05	0.04	0.39
Single Residents (Share)	0.30	0.12	0.11	0.77
Married Residents (Share)	0.38	0.09	0.12	0.56
Foreign Residents (Share)	0.15	0.10	0.01	0.53
Panel E. Area Characteristics				
Distance to City Center (km)	16.88	15.38	0.12	87.57
Residential Address Share (Percent)	61.74	17.62	0.00	86.04
Mixed-Use Address Share (Percent)	18.34	13.71	0.00	73.06
Commercial Address Share (Percent)	5.65	5.61	1.04	61.00
Panel F. Industry Composition				
Firms (Number)	1255.71	918.00	88.00	10914.00
Firm Density (Number per Inhabitant)	0.10	0.37	0.01	9.21
Manufacturing Firms (Share)	0.04	0.02	0.01	0.11
Food and Accommodation Firms (Share)	0.03	0.02	0.01	0.20
ICT Firms (Share)	0.04	0.02	0.00	0.13
Retail Firms (Share)	0.15	0.03	0.05	0.30
Financial Firms (Share)	0.05	0.02	0.01	0.14

Notes: The table reports summary statistics for 810 postcodes included in our sample. Payment data are from Mastercard (Panel A). WFH data and other postcode characteristics are collected and provided by infas360 (Panels B, C, D, and F). Area characteristics are based on administrative data (Panel E).