The Impact of Telework on Local Consumption*
Evidence from Mobile Phone and Transaction Data

Gabrielle Gambuli†[1], David Bounie[1], Chloé Breton[1], and Etienne Côme[2]

[1]Télécom Paris, CREST
[2]Université Gustave Eiffel, GRETTIA

January 21, 2026

Abstract

While prior studies have examined how telework affects consumer spending either near residences or workplaces, its net economic impact remains unclear. Using mobile phone data and card transaction records from the Lyon metropolitan area, France's second-largest, we show that a 1pp increase in working-from-home presence raises local spending by 1%, while a 1pp increase in workplace absence reduces it by 1.3%. Aggregating these opposing effects implies a net 3% decline in aggregate weekday consumption, reflecting incomplete substitution. Effects are spatially heterogeneous – urban cores lose while residential suburbs gain – and sectoral, as spending shifts from restaurants toward bars and food retail.

Keywords: Remote work, Work from home, Consumer mobility, Economic Geography, Card transaction data, Mobile phone data

JEL Codes: R11, R12, J22, L81

*This research was supported by the ANR MobiTIC project (grant number ANR-19-CE22-0010), a collaborative initiative between Orange, Université Gustave Eiffel, and INSEE, and by the Research Chair Digital Finance under the aegis of the Risk Foundation, a joint initiative by Groupement des Cartes Bancaires CB, Telecom Paris and University Paris-Panthéon-Assas. The findings and interpretations expressed herein are solely those of the authors and do not reflect the positions of the affiliated institutions. We would like to thank John Galbraith who meticulously followed our progress on this project and continuously enriched our discussions, and also Michael Stops for his rigorous discussion of our paper at the 14th European Meeting of the Urban Economics Association. We are finally grateful for the feedback and questions from attendees at conferences including MNO-MINDS Final Conference (Eurostat CROS), 11th AFREN Digital Economics Conference, 2025 Télécom Paris Research Retreat, 73rd Congress of the AFSE, and the 14th European Meeting of the UEA.

†The author primarily conducted this research while at Université Gustave Eiffel. Her current address is Télécom Paris. Contact: gabrielle.gambuli@gmail.com

1 Introduction

The COVID-19 pandemic accelerated the adoption of hybrid work,[1] where employees split their time between home and office. In France, the share of workers teleworking at least one day per week[2] surged from 3% in 2017 to 20% in 2024, with teleworkers now averaging two to three days working from home (Enquête Emploi, INSEE).[3] This rapid and enduring shift, far from a temporary response to the pandemic, represents a structural transformation of urban economies, with profound implications for city centers, retail sectors, and spatial inequality.

Yet while telework has become a permanent feature of the labor market, its broader economic consequences, particularly its impact on local consumption, remain poorly understood. How does telework reshape the spatial and temporal distribution of spending within urban areas? Does it merely redistribute consumption from business districts to residential neighborhoods, or does it also alter the overall volume of economic activity? Which localities and sectors stand to gain or lose from this transformation, and what are the net effects on aggregate spending? Answering these questions is critical for policymakers, businesses, and urban planners navigating the post-pandemic economy, as well as for understanding the broader economic geography of cities.

To empirically address these questions, we focus on the Lyon metropolitan area, France's second-largest, which comprises 560 municipalities and has a total population of 2.4 million residents. The region's structure, a dense urban core surrounded by an extensive commuting zone, makes it an ideal case study for analyzing the demand shocks generated by telework. Given this spatial configuration, we examine how telework affects both high-density urban centers and peri-urban areas, providing a comprehensive view of its economic and geographic impacts. Specifically, we investigate how the increased presence of workers at home and their reduced presence at workplaces alter the geography of consumption on weekdays,[4] affecting retail activity, service industries, and spatial inequality.

To capture these dynamics with precision, we leverage two unique and highly granular datasets. First, we use mobile phone location data, which tracks individuals' presence across space and time. This allows us to estimate daily patterns of teleworkers' home presence and workplace absence. Second, we employ card transaction data, which records daily in-person spending in physical establishments such as retail stores, restaurants, and cafés. Our combination of high-frequency mobile phone data and transaction records enables us to analyze telework's impact at the municipality-day level. By integrating these datasets over 28 consecutive days in September 2022, specifically the 20 weekdays across four weeks, we directly link telework behavior to observed consumption patterns at this fine spatial and temporal scale.

[1] In this paper, we use the terms hybrid work, working from home, remote work, and teleworking interchangeably. Following common usage in the literature, teleworking generally refers to performing job tasks outside the primary workplace, typically from home. Hybrid work denotes a flexible arrangement where employees split their time between the office and remote locations. Working from home specifically indicates days spent completing work tasks at the residence rather than the office. Remote work is a broader term encompassing both teleworking and hybrid arrangements. In this paper, we focus on hybrid work arrangements, the predominant form of flexible work in France, and assume that when employees are teleworking, they work from home.

[2] In this paper, we refer to those employed individuals who work from home at least once per week as "teleworkers".

[3] The Enquête Emploi en continu is France's continuous labour-force survey conducted by Insee. Its sample is drawn at the dwelling level and is implemented year-round, with roughly 80,000 dwellings surveyed in 2024; see Table 11 for annual telework statistics.

[4] In Section 5.2, we also examine whether telework induces intertemporal substitution between weekdays and weekends. We find that municipalities with a higher share of residents teleworking on weekdays exhibit a relatively higher share of spending on weekdays compared with weekends.

Building on these fine-grained data, our identification strategy exploits daily variation in telework intensity and offline consumption within municipalities in a two-way fixed effects framework. Telework simultaneously increases workers' presence at home and reduces their presence at workplaces, generating two distinct local demand shocks. By combining mobile phone data with labor force survey and population census records, we separately measure these home-presence and workplace-absence shocks, allowing us to identify the causal effect of telework on local consumption with limited bias and to recover its net impact on aggregate weekday spending within a large metropolitan area.

We implement this identification strategy in three steps. First, we estimate the share of teleworkers in each municipality of residence and workplace by projecting telework practices inferred from the labor force survey onto the working population observed in the population census. We find that 60% of teleworkers reside in the urban core, while 70% are employed there, revealing a spatial mismatch that implies telework does not simply shift demand from city centers to suburbs.

Second, we use high-frequency mobile phone presence count data to estimate daily telework intensity by weekday. We use variation in the number of residents present in their home neighborhoods during working hours across weekdays to infer daily telework patterns. By exploiting this systematic within-week variation and accounting for confounding factors, such as part-time workers on their days off, we recover daily average telework rates that exhibit pronounced peaks on Wednesdays and Fridays. This reflects firm and worker scheduling decisions, therefore plausibly exogenous to short-term shocks to retail activity.

Finally, we estimate the causal impact of telework-induced demand shocks on local consumption by combining daily telework measures with municipality-level exposure at both places of residence and work in a Pseudo Poisson Maximum Likelihood (PPML) model with two-way fixed effects. These fixed effects control for time-invariant municipality characteristics and systematic day-of-week patterns, while observable confounders are explicitly accounted for, such as the presence of part-time workers. Together, these design features support a causal interpretation of the estimated effects and enable us to measure the net impact of telework on weekday offline consumption, at both the municipality and regional levels, by comparing model-predicted spending under observed telework levels with a model-implied no-telework benchmark, holding all other factors constant.

Our analysis yields five key findings with significant implications for urban policy and economic geography. First, telework generates dual demand shocks, increasing consumption at home while reducing it at workplaces. Specifically, a one-percentage-point increase in the share of resident workers working from home is associated with a 1% increase in local transaction value (significant at the 1% level). Conversely, a one percentage point increase in the share of workers absent from their workplace due to telework corresponds to a 1.3% decrease in spending. This asymmetry highlights how telework simultaneously stimulates and suppresses local economic activity, challenging the assumption that it merely redistributes consumption without affecting total economic activity.

Second, telework induces partial consumption substitution: a 1-percentage-point increase in home presence offsets only 72% of the losses from a 1-percentage-point increase in workplace absence. Our results provide the first direct evidence that substitution is incomplete, leading to a net decline in aggregate spending. When measured in terms of transaction count rather than values, the substitution rate falls to 57%, suggesting that while the monetary volume of spending is better preserved, the number of transactions declines more sharply. This discrepancy likely reflects differences in consumption patterns, such as fewer but larger purchases near home compared to more frequent, smaller transactions near workplaces.

Third, telework drives a spatial redistribution of consumption from the urban core to the commuting zone. Our analysis reveals that 60% of municipalities within the Lyon metropolitan area experience a decline in sales relative to a zero-telework scenario.[5] The urban core suffers the largest losses, particularly in Lyon city,

Fourth, telework leads to a net reduction in aggregate transactions on weekdays, with its impact varying by urban centrality. The estimated aggregate effect is consistently negative across all zone groups, though the magnitude of the reduction increases with proximity to the urban core. For example, transaction values decline by 3% in the urban core (including Lyon city and its inner ring), by 2% in the urban commuting zone, and by less than 1% in the rural commuting zone, highlighting that denser areas bear the brunt of telework's economic impact. This pattern underscores the uneven spatial distribution of telework's effects, with central areas experiencing the largest losses.

Fifth, telework generates sector-specific shifts in consumption. The effect is highly heterogeneous across sectors and space. Restaurants experience the largest declines, with transaction values falling by 21%, particularly in the urban core, which alone accounts for 74% of the overall losses across the metropolitan area and 50% within Lyon city proper. By contrast, bars and cafés benefit from telework, emerging as local substitutes for socializing and remote work, with sales increasing by 16%. Similarly, food retail experiences gains in transaction value (+3%), driven by larger basket sizes as the number of shopping trips declines slightly (-2%). Together, these patterns illustrate a reallocation of spending from city-center restaurants to cafés and grocery consumption in residential and peri-urban areas, reflecting how telework reshapes both the composition and geography of local consumption.

To ensure the robustness of our findings, we conduct a series of additional tests, all documented in Appendix C.2 that address potential econometric concerns through three complementary approaches. First, we conduct rigorous robustness checks including multicollinearity diagnostics and alternative telework measures that exclude potential double-counting, while controlling for part-time workers, weather, and transport disruptions. Second, we perform extensive sensitivity analyses using standardized telework shares, measurement error simulations, and alternative measurement approaches that all yield qualitatively consistent results. Finally, we complement our main analysis with an IV strategy to address potential endogeneity arising from measurement error in our telework indicators. Following a shift-share design, we exploit two sources of exogenous variation: (i) deviations in the distribution of teleworkers across home and workplace locations relative to pre-pandemic levels, when telework was marginal (about 3% of workers), and (ii) differences in daily stay-at-home patterns between teleworkers and executive part-time workers, who are otherwise similar but differ in the number of days spent at home. These deviations are plausibly exogenous, as they are mechanically determined by the pre-existing spatial distribution of teleworkable jobs and residences and affect local consumption only through telework. Estimates from this IV approach closely align with our baseline results, further reinforcing the robustness of our findings. The remarkable consistency across these diverse validation approaches significantly strengthens the credibility of our causal interpretations regarding telework's impact on local consumption patterns.

[5] We estimate the causal impact of telework on weekday offline consumption by computing the difference (in levels and percentage) in the predicted spending under observed telework levels with a no-telework benchmark generated by the model, holding everything else constant.

Building on our core findings, we further explore two dimensions of telework's impact on consumption: spatial spillovers and intertemporal substitution. First, we account for spatial spillovers by examining whether teleworkers' consumption extends beyond their home or workplace municipalities. We estimate a spatial model that interacts telework indicators with a contiguity matrix, revealing that demand spills over to neighboring areas. This likely occurs because teleworkers, benefiting from reduced commuting time, allocate spending to locations along their revised activity patterns. This result aligns with prior evidence showing that daily traveled distances did not decrease as much as commuting distances (Hostettler Macias et al., 2022; Kiko et al., 2024), suggesting that teleworkers redistribute, rather than reduce, their mobility and consumption across space. Second, we analyze intertemporal consumption substitution by examining shifts in the timing of spending. We find that municipalities with higher concentrations of resident teleworkers tend to exhibit relatively lower weekend spending compared to weekdays, suggesting that teleworkers reallocate part of their shopping and leisure activities from weekends to weekdays. This pattern remains robust after accounting for municipality and date fixed effects in our empirical model. Together, these findings suggest that telework not only impacts the spatial distribution of consumption by redirecting demand to neighboring areas but also alters its temporal dynamics, as workers reallocate spending from weekends to weekdays. These transformations provide a more nuanced and comprehensive understanding of how telework influences urban economic activity.

Our study builds on and extends the growing literature on telework and urban economics by providing the first comprehensive, two-sided assessment of telework's impact on local consumption. In doing so, we advance two particularly influential studies: Alipour et al. (2022) and Althoff et al. (2021), both of which have significantly contributed to our understanding of the spatial economic consequences of telework. Alipour et al. (2022) examine the effect of telework potential at residence on local spending using a difference-in-differences (DiD) design comparing areas with high versus low telework potential over pre- and post-covid periods. They find that higher numbers of teleworkers at home are associated with increased spending in the home neighboring. However, their analysis did not account for the offsetting losses from workplace absence, which are essential for a complete causal interpretation of telework's net effects on local consumption. Similarly, Althoff et al. (2021) focuses on the U.S. context, emphasizing declines in business district spending using cross-sectional variation in telework potential, similar to Alipour et al. (2022), but from the perspective of jobs rather than residences. Yet, their work did not directly measure the redistribution of consumption between residential and workplace areas or the net effects on local economic activity. By integrating these dimensions into a unified framework, our study builds on their foundational contributions by simultaneously quantifying the positive demand shocks from increased home presence and the negative shocks from workplace absence. Together, these advancements provide a more comprehensive and nuanced picture of how telework reshapes urban economic landscapes, addressing questions that prior studies could not fully explore.

We also introduce a novel approach to measure telework practices and their effects on offline consumption by exploiting an unprecedented combination of high-frequency mobile phone location data and detailed card transaction records. This enables analysis at the municipality-day level and captures within-week variation in telework intensity, with peaks on Wednesdays and Fridays. Our two-way fixed effects model leverages this daily variation to isolate the causal effects of telework, addressing endogeneity concerns more rigorously than Alipour et al. (2022) and Althoff et al. (2021). Using this approach, we provide the first empirical evidence that substitution between home- and workplace-based consumption is incomplete, leading to a net decline in aggregate spending. This result has important implications for theories of consumption behavior and urban economic geography.

Related literature. Our study contributes to a rapidly growing literature on the economic and spatial consequences of telework. A first strand examines how telework reshapes urban structure and mobility patterns. By reducing commuting flows and peak-hour congestion (Delventhal et al., 2022; Kiko et al., 2024), telework alters individuals' daily time allocation and the geography of their activities. In the U.S., these adjustments have interacted with housing markets, triggering residential relocations from dense urban cores toward suburban areas—the well-documented "donut effect" (Ramani and Bloom, 2021; Behrens et al., 2024; Gokan et al., 2022; Li and Su, 2026). These migration patterns mechanically reallocate local demand and modify the spatial distribution of housing as well as office needs, with measurable consequences for real estate prices and commercial rents, particularly in city centers and high-amenity neighborhoods (Althoff et al., 2022; Delventhal et al., 2022; Dalton et al., 2023; Kyriakopoulou and Picard, 2023; Li and Su, 2026). In contrast, European settings display much weaker migration responses, even in metropolitan areas where telework is widespread, as documented by the GIP POPSU Territoires (2022) in France and by Alipour et al. (2022) in Germany. Alipour et al. (2022) show that short-run adjustments operate mainly through changes in daily routines rather than residential mobility. This distinction is central for our identification strategy. By focusing on September 2022, we abstract from medium-run sorting or real-estate adjustments, which can reasonably be considered fixed over this short horizon. We thus measure the effect of telework on consumption driven purely by daily changes in the spatial distribution of workers between their residence and workplace.

A second strand of research investigates how telework reshapes local urban economies and commercial activity, to which our paper contributes by providing high-frequency evidence on daily consumption responses. Using data from the Paris region, Denagiscarde (2025) document that higher telework intensity (from the workplace vision) reduces office occupancy and depresses the number of proximate consumer service establishments. These effects are consistent with Bergeaud et al. (2021), who document rising vacancy rates, reduced construction activity, and falling prices in the French office market. Similar patterns emerge in the U.S., where Dalton et al. (2023) find substantial employment losses in accommodation, food services, and retail in areas most exposed to telework adoption. Complementing this evidence with survey data, De Fraja et al. (2026) show that permanent increases in remote working lead to large reductions in local personal services spending in England and Wales: neighborhoods where people commute 20% less experience a 5% decline in local personal services expenditure, with sharp losses in city centers and more dispersed gains in peripheral areas, which closely aligned with our findings. Our work also relates to Miyauchi et al. (2025), who develop a theoretical framework to model travel itineraries, i.e. multi-stop trips that include work, shopping, and leisure, and demonstrate how these itineraries generate consumption externalities and agglomeration forces in cities. While they use the shift to working from home during the COVID-19 pandemic as a quasi-experimental case to validate their model, their focus is on the broader implications of spatial mobility for urban structure and transport policy, rather than the causal impact of telework on local consumption, which is the focus of our paper.

Our work also contributes to the literature on the welfare of workers to teleworking. Survey evidence from Barrero et al. (2021) shows that teleworkers report tangible economic benefits. Among the most frequently cited benefits are reduced commuting and lower lunch and gasoline expenses, patterns that align with our finding of decreased offline spending, particularly in restaurants. Barrero et al. (2021) further document that workers are even willing to accept wage cuts to retain telework arrangements, underscoring perceived welfare gains. However, the welfare implications of telework may not be uniformly positive: Goux and Maurin (2025) report deteriorating health outcomes among teleworkers.

Finally, our paper contributes to the measurement of telework practices at high spatial and temporal resolution. By combining mobile phone data with labor force and census information, we construct a fine-grained, behaviorally informed measure of how telework reshapes individuals' daily presence. In contrast, prior research has largely depended occupation-based measures, including the widely used teleworkability index of Dingel and Neiman (2020). Another approach relies on aggregated mobile phone data, such as the Google Mobility Index or the Economist Normalcy Index, which track changes in presence at residences and workplaces relative to the pre-COVID-19 period, typically at the country or regional level. Survey-based assessments have also been combined with aggregated mobile phone data (Buckman et al., 2025), where any shortfall in workplace presence relative to pre-pandemic benchmarks is interpreted as work-from-home. While these proxies have been invaluable for capturing broad patterns, they typically offer either coarser spatial detail or lower temporal frequency, which our approach overcomes.

The remainder of the paper is organized as follows. Section 2 describes the data. Section 3 details the construction of daily telework measures. Section 4 outlines the empirical strategy to measure the causal impact of telework on local consumption. Section 5 extends the analysis to spatial spillovers and intertemporal substitution. Section 6 concludes.

2 Data on Telework and Local Consumption

This section presents the datasets used to quantify telework's impact on local consumption by leveraging in particular two complementary high-frequency data sources: (1) mobile phone geolocation data (Orange) tracking individuals' daily presence in their residential and workplace municipalities, and (2) debit/credit card transaction records (Groupement des Cartes Bancaires CB) detailing in-person spending by sector, municipality, and day. This municipality-day-level fusion of mobility and transaction data, covering 560 municipalities in the Lyon Functional Urban Area over September 2022, enables us to isolate the dual demand shocks generated by telework (increased home presence vs. reduced workplace presence) and analyze their spatial and sectoral redistribution effects on urban consumption.

Sample. Our sample includes observations at the municipality level in the Functional Urban Area (FUA) of Lyon, the second-largest in France and among the top twenty in Europe by population. An FUA is composed of two main components, following the OECD definition: (1) an urban core, defined as a high-density area with at least 50,000 inhabitants, based on population density and built-up continuity; and (2) its commuting zone, composed by surrounding municipalities where a significant share of the working population commutes to the urban core for work, typically above a 15% threshold. The Lyon FUA, shown in Appendix A.1 in Figure 4, comprises 560 municipalities and hosted 2.7 million residents and 1.2 million workers in 2022. The urban core alone, composed by Lyon city and its little crown, concentrates around 50% of the population and 60% of the jobs, making it a highly polarized economic center.

To capture the spatial and temporal dynamics of telework, we combine three datasets: (1) mobile phone location data (Orange) to estimate daily telework patterns by tracking individuals' presence in residential zones during working hours, (2) labor force surveys (Insee's Enquête Emploi) to assess structural telework potential by occupation and location, and (3) population census records to map commuting flows and workplace distributions across municipalities.

Mobile phone presence data. We use mobile phone data from *Orange*, France's leading mobile operator, which provide aggregated presence count every 30 minutes over 28 consecutive days in September 2022 within each Iris[6] zones of Lyon FUA. Raw data consist of high-frequency records of SIM card detections by mobile antennas, which are projected onto Iris zones and aggregated accordingly by Orange. Counts are then adjusted to approximate actual population volumes, correcting for differences in mobile phone penetration across population demographic groups and for the operator's market share. The data are truncated to a minimum of 20 individuals per observation for confidentiality reasons, ensuring that no individual can be identified or tracked. The data is segmented by residential zones,[7] allowing us to quantify the number of residents who are present in their home neighborhoods every 30-minute intervals. Variation in presence count in home neighborhoods during working hours across weekdays is used to infer daily telework patterns, as detailed in Section 3.2. In Appendix A.2, we present a descriptive analysis of the variation in the number of people present in their residential areas during weekdays over working hours, highlighting the potential of mobile phone data to capture how teleworking affects commuting patterns and real-time population densities.

Population Census. We use the 2021 Population Census from Insee as the backbone of our analysis. The census provides a detailed matrix of the count of workers by municipality of residence, workplace, and occupation within the Lyon Functional Urban Area (FUA).

Labor Force Survey. To estimate telework and part-time work patterns, we use data from the *Enquête Emploi en Continu* (EEC, Q4 2022) from Insee. The EEC covers individuals aged 15 to 89 living in ordinary private dwellings in metropolitan France (excluding the French Overseas Departments and Territories). This annual survey includes approximately 80,000 dwellings (sampling rate of 1 in 400) and provides information on occupation, residential location, and telework. We compute Auvergne-Rhône-Alpes regional averages of the telework share by occupation and by residential location type within Functional Urban Areas. Occupation is classified into six broad groups: (1) Farmers; (2) Craftsmen, shopkeepers, and business owners; (3) Managers and higher-level intellectual professions; (4) Intermediate professions; (5) Clerical and service employees; and (6) Manual workers. Residential location within FUAs is grouped into four categories: city center, inner suburbs, outer suburbs, and outside the FUA. These categories reflect differences in both task-based telework feasibility (occupation) and spatial access to jobs (residence within FUAs), while remaining broad enough to ensure reliable average telework rates. [8]

The resulting national telework averages are then applied to the census residence-workplace-occupation matrix. Specifically, each worker's municipality of residence and occupation determines the expected number of teleworkers by municipality of residence and by workplace. This projection forms the basis of our daily telework estimation. Similarly, the EEC provides data to compute national daily averages of the share of part-time workers who are typically off work from Monday to Friday, by occupation and residential location type within FUAs. These shares are applied to the number of part-time workers in each census cell to estimate, for each day of the

[6]The Iris zones (Ilots Regroupés pour l'Information Statistique) are sub-municipal geographic units defined by geographic and demographic criteria. These zones are defined within municipalities with at least 10,000 inhabitants, and within a significant proportion of municipalities having between 5,000 and 10,000 inhabitants. An Iris' population typically ranges from 1,800 to 5,000 inhabitants.

[7]The residential zones are defined by Orange as groups of contiguous Iris zones where individuals spend most of their nighttime (midnight to 6 a.m.) the day before.

[8]It was not possible to compute the same shares by workplace location groups, as this information is missing in the version of the survey available to us.

week, the number of part-time workers likely to be present at home or absent from their workplace. These estimates are included as controls in both the daily telework estimation model and the consumption model.

Finally, we measure local consumer spending using anonymized payment card transaction data.

Card transaction data. We use data from Groupement des Cartes Bancaires CB,[9] the domestic card payment system in France. In 2022, card payments accounted for 62.6% of the total number of payment transactions in France (including cheques, bank transfers, direct debits, and electronic money) when using cards issued by resident payment service providers, according to the *European Central Bank's Payments and Settlement Systems Statistics*. In practice, most bank cards issued in France, often co-branded with Visa or Mastercard, operate through the CB network when used domestically. The raw data includes detailed records of each transaction, including the date and time, as well as the establishment code[10] of the point of sale, which allows us to identify the sector of activity (Nomenclature d'Activités Française (NAF codes) produced by INSEE) and the geographic location of the establishment. We restrict the sample to on-site transactions (excluding on-line transactions) and to seven key retail and service categories: Restaurants, Food Retail, Bars and Drinks, General Retail, Clothing and Beauty Retail, Sports and Recreation, and Health and Wellness Retail. We aggregate transaction count and value by sector of activity, municipality, and day in September 2022. For municipality $\times$ date $\times$ sector combinations not observed in the data, we assume zero spending. On a typical weekday in September 2022, over 800,000 in-person transactions are recorded, with a total value of 26 million euros. The urban core accounts for roughly 50% of total spending and 57% of all transactions. Over a typical week, spending is higher on Wednesdays and Fridays (see Figure 6 in Appendix A.3).

3 Measuring Spatial and Temporal Patterns of Telework

This section empirically assesses the spatial and temporal patterns of telework in the Lyon metropolitan area using labor force surveys, census records, and mobile phone presence data. First, we estimate the structural potential for telework at both the residence and workplace levels, quantifying the share of workers expected to telework in each municipality. Second, we develop a daily telework model that leverages mobile phone data to estimate the share of teleworkers working from home each weekday, explicitly accounting for confounding factors such as the presence of part-time workers on their days off. Finally, we use these estimates to construct approximated telework shares by municipality and day from both residential and workplace perspectives, that will be used in the causal analysis presented in Section 4.

3.1 Geography of Teleworkers' Residence and Workplace

We estimate the potential for telework across the Lyon FUA by combining labor force survey data and population census for workers distributions across their residence and workplace. Using the French Labor Force Survey (EEC, Q4 2022), we compute the share of teleworkers, τ_{kg}, in each

[9]These data were made available thanks to a partnership with Groupement des Cartes Bancaires CB, and we exploit the card payments data in accordance with the EU General Data Protection Regulation, in application of Article 89. We use the abbreviation 'CB' to indicate the source of the card payments.

[10]The establishment code is a unique 14-digit identifier assigned to every business establishment in France and registered in the *Système d'Identification du Répertoire des Établissements* (SIRET).

occupation k residing in location type g (urban core, inner suburbs, outer suburbs, and outside FUA). The resulting values are reported in Table 11 in Appendix B.1. We then combine these shares with commuting patterns (residence i to workplace j) from the 2021 Population Census to compute, for each municipality, its exposure to telework, both from the perspective of where workers live and where they work:

$$\mathrm{TE}_i^{(\mathcal{H})} = \frac{\sum_{jk} \tau_{gk} \mathrm{Workers}_{ijk}}{\mathrm{Workers}_i^{(\mathcal{H})}} \tag{1}$$

$$\mathrm{TE}_j^{(\mathcal{W})} = \frac{\sum_{igk} \tau_{gk} \mathrm{Workers}_{ijk}}{\mathrm{Workers}_j^{(\mathcal{W})}} \tag{2}$$

where $\mathrm{Workers}_{ijk}$ denotes workers in occupation k, living in municipality i and employed in j; $\mathrm{Workers}_i^{(\mathcal{H})} = \sum_{jk} \mathrm{Workers}_{ijk}$ denotes the total amount of workers living in i ($\mathcal{H}$ for home); $\mathrm{Workers}_j^{(\mathcal{W})} = \sum_{ik} \mathrm{Workers}_{ijk}$ denotes the total amount of workers employed in j ($\mathcal{W}$ for workplace); $\mathrm{TE}_i^{(\mathcal{H})}$ is the telework exposure at home and is computed as the share of workers residing in municipality i (where i belongs to location type g) who are expected to telework and may therefore be present at home during working hours at least once per week; $\mathrm{TE}_j^{(\mathcal{W})}$ is the telework exposure at the workplace and is computed as the share of workers employed in municipality j who are expected to telework and may therefore be absent from their workplace at least once per week

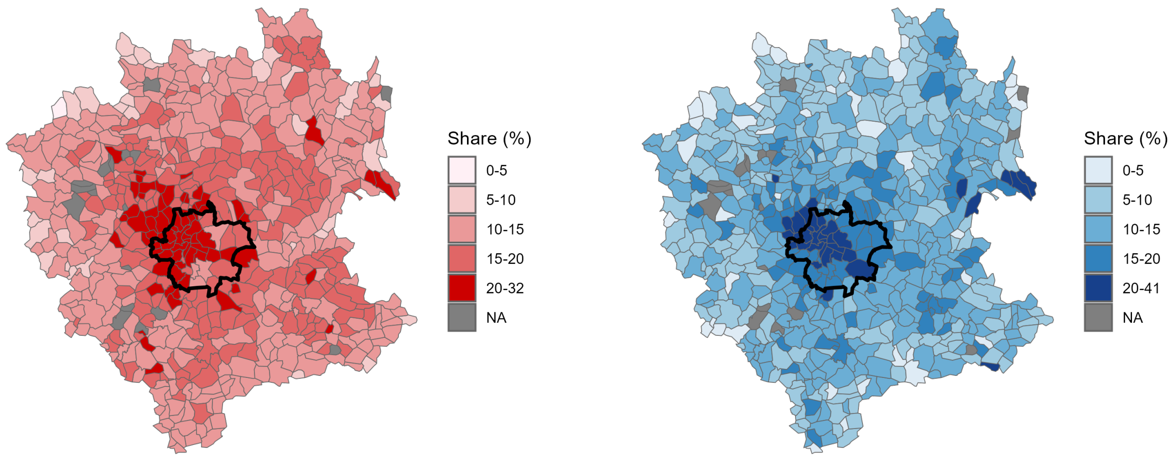
Based on this approach, we estimate approximately 220,000 teleworkers in the Lyon area, of whom 60% reside in the urban core and 70% are employed there. Figure 1 presents the distribution of teleworkers as shares of workers by both their place of residence and workplace. According to the figure, the expected impact of telework on consumption is not simply a matter of shifting spending from workplaces in the city center to residential areas in the suburbs, as often reported in the literature. In fact, the spatial reality is more complex. First, most teleworkers both live and work within the urban core. Second, teleworkers are more spatially dispersed by place of residence than by place of work. Third, some municipalities in the commuting zone exhibit notably high teleworkers shares with respect to both places of residence and work.

3.2 Daily Rhythms of Telework: When People Work from Home

We examine now the temporal dimension of telework by estimating daily rates at the municipality level. Using mobile phone data, we track the presence of individuals in their residential areas during working hours and develop a model to estimate the share of teleworkers working from home each weekday. This model accounts for confounding factors, such as the presence of part-time workers on their days off, to isolate the effect of telework.

The model specifies residential presence as a function of three population groups: inactive individuals, part-time workers on their day off, and teleworkers working from home. Crucially, we account for the daily variation in the share of part-time workers on day-off, who may stay at home for reasons unrelated to telework but whose presence patterns could otherwise confound telework estimates. The model is written as follows:

$$\mathrm{Residents}_{it} = \widehat{\alpha}\ \mathrm{Inactives}_i + \sum_k \gamma_{gkt}\ \text{Part-time workers}_{ik} + \sum_t \widehat{\beta}_t \mathbb{1}_t\ \mathrm{Teleworkers}_i + \epsilon_{it} \tag{3}$$



(a) home (b) workplace

Note: The left panel shows the municipality-level share of employed residents who may be present at home when teleworking (Eq. 1). The right panel shows the corresponding share of workers who may be absent from their workplace when teleworking (Eq. 2).

Figure 1: Teleworkers share, $\text{TE}_i^{(\mathcal{H})}$ and $\text{TE}_j^{(\mathcal{W})}$

where Residents_{it} is the average daily count of residents[11] present in their nighttime zone i (Iris) during working hours on day t, averaged over four weeks of September 2022 using the Orange mobile phone data. Inactives_i and Part-time workers_{ik} denote respectively the inactive population (unemployed, students, housewives/husbands, retirees, etc.) and part-time workers by occupation k residing in Iris zone i, derived from census data. γ_{gkt} represents the day- and occupation-specific presence rate of part-time workers living in location type g (urban core, inner suburbs, outer suburbs, and outside the functional urban area), estimated from labor force survey data and presented in Figure 8 in Appendix B.2. Teleworkers_i is the teleworker population in Iris zone i, computed using combined census and labor survey data. $\widehat{\alpha}$ and $\widehat{\beta}_t$ are the parameters to be estimated in the model, capturing respectively the daily share of inactive residents at home (assumed constant across days) and the daily telework rate of teleworkers working from home. Model parameters are estimated using Ordinary Least Squares (OLS).

Table 1 presents the estimated daily shares of teleworkers working from home (model 3). The results (column 1) indicate that the average share of teleworkers working from home is 51.7% on Monday, 25.6% on Tuesday, 62.3% on Wednesday, 24.1% on Thursday, and 77.9% on Friday. The sum of these daily shares amounts to 2.4 days per week, matching the Auvergne-Rhône-Alpes region average from the Labor Force Survey, suggesting our method reliably captures realized telework patterns. Further validation against on-site attendance data from a Paris-based public institution (October 2022–February 2024) shows close alignment with our estimates, reinforcing the robustness of our results (see Appendix B.3).

[11] Using mobile phone data, we compute the share of residents present in their nighttime zone during working hours (9 a.m. to 12 p.m.) by comparing morning presence count to those at 6 a.m. on the same day. This avoids bias from Orange's resident definition, which is based on the previous night. The 6 a.m. reference minimizes errors due to antenna standby during the night. We then multiply these shares by the census population of each Iris zone to align presence count with inactives, teleworkers and part-time workers population levels in the model. Census figures may include decimals, as they partly rely on survey estimates.

Dependent Variable:	Residents in their nighttime zone net of part-time workers on day off		
Model:	(1)	(2)	(3)
	All FUA	Urban core	Commuting zone
Inactive population	1.03***	0.960***	1.08***
	(0.029)	(0.038)	(0.058)
Teleworkers × Monday	0.517***	0.684***	0.620−
	(0.159)	(0.179)	(0.433)
Teleworkers × Tuesday	0.256+	0.482***	0.181
	(0.163)	(0.184)	(0.434)
Teleworkers × Wednesday	0.623***	0.776***	0.766*
	(0.166)	(0.186)	(0.445)
Teleworkers × Thursday	0.241+	0.470**	0.156
	(0.162)	(0.183)	(0.435)
Teleworkers × Friday	0.779***	0.974***	0.795*
	(0.162)	(0.183)	(0.434)
Number of teleworked days (reference = 2.428)			
Inferred from estimates ($\sum_t \widehat{\beta}_t$)	2.417	3.387	2.518
Fit statistics			
Observations	5,462	2,513	2,949
R^2	0.77880	0.66060	0.85897

Note: Signif. codes: ***: 0.01, **: 0.05, *: 0.1, +: 0.15, -:0.2. Clustered standard-errors at the Iris zone level in parentheses. The reference number of teleworked days (conditional on teleworking) reported in the table, used to validate our results, is calculated from the Q4 2022 Labor Force Survey (*Enquête Emploi en Continu*) for the Auvergne-Rhône-Alpes region, which encompasses the Lyon FUA.

Table 1: Estimated Share of Teleworkers Working from Home by Day of Week and Zone

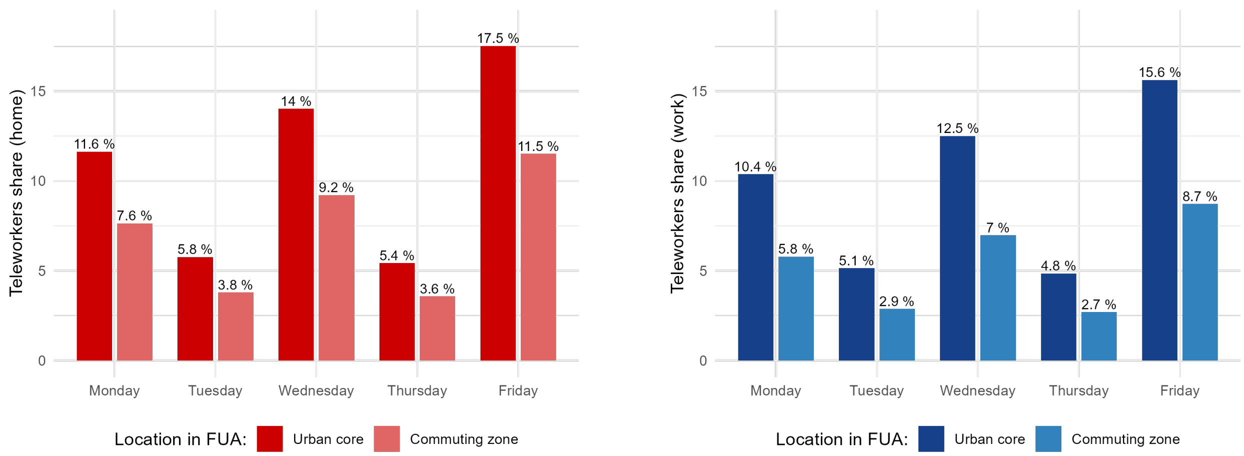
Splitting the sample between municipalities in the urban core (column 2) and those in the commuting zone (column 3) reveals that the intensity of telework is significantly higher in the urban core for each weekday, with the highest levels of work from home observed on Fridays and Wednesdays. By contrast, the weekly pattern in the commuting zone is flatter and estimated with less precision, although Friday and Wednesday still emerge as the main telework days. The inferred number of teleworked days per week ($\sum_t \hat{\beta}_t$) confirms this contrast: teleworkers based in core municipalities are estimated to work remotely 3.4 days per week on average, compared to 2.5 days in the commuting zone.[12]

Using the estimated $\widehat{\beta}$, we can compute the realized telework shares – the daily shares of all employed workers working from home – for each municipality and day both from the residence perspective, $\mathrm{RT}_{it}^{(\mathcal{H})} = \widehat{\beta}_t \mathrm{TE}_i^{(\mathcal{H})}$, and workplace perspective, $\mathrm{RT}_{jt}^{(\mathcal{W})} = \widehat{\beta}_t \mathrm{TE}_j^{(\mathcal{W})}$. Since the average working from home daily shares (conditional on teleworking) sum to 2.4, consistent with the average number of teleworked days reported by teleworkers in the Labor Force Survey, the estimates presented in column (1) of Table 1 are considered our preferred specification. Later on, we construct alternative indices that account for the differing working-from-home daily shares observed between municipalities in the urban core and those in the commuting zone for robustness test.

Figure 2 presents the average daily estimated telework shares – shares of workers working

[12]Some daily shares in the commuting zone sample are not significantly different from zero, which explains the difference between the overall average in column 1 and the averages in columns 2 and 3.

from home – $\mathrm{RT}_{it}^{(\mathcal{H})}$ and $\mathrm{RT}_{it}^{(\mathcal{W})}$ for municipalities in the urban core and the commuting zone, separately for residence and workplace locations. Telework shares are consistently higher in the urban core, and daily fluctuations are more pronounced than in the commuting zone. For instance, the share of workers present at home teleworking ranges from 5.4% on Thursday to 17.5% on Friday in the urban core, compared to a narrower range of 3.6% to 11.5% in the commuting zone. Daily telework shares based on workplaces are systematically lower than those based on residences, reflecting the higher spatial concentration of teleworkable jobs compared to where teleworkers live.



(a) home

(b) workplace

Note: The left-hand figure shows the average municipal share of employed residents teleworking on each weekday, who are likely to spend the day at home, comparing the FUA urban core and the commuting zone. The share is computed as $\mathrm{RT}_{it}^{(\mathcal{H})} = \widehat{\beta}_t \mathrm{TE}_i^{(\mathcal{H})}$, where $\mathrm{TE}_i^{(\mathcal{H})}$ is defined in Equation 1. The right-hand figure shows the average municipal share of employed workers teleworking per weekday, and thus who may be absent from their official workplace. The share is computed as $\mathrm{RT}_{jt}^{(\mathcal{W})} = \widehat{\beta}_t \mathrm{TE}_j^{(\mathcal{W})}$, where $\mathrm{TE}_j^{(\mathcal{W})}$ is defined in Equation 2.

Figure 2: Average teleworkers share, $\mathrm{RT}_{it}^{(\mathcal{H})}$ and $\mathrm{RT}_{it}^{(\mathcal{W})}$, by day and zone

4 The Causal Impact of Telework on Daily Spending

This section investigates the causal impact of telework on local consumption by leveraging the spatial and temporal patterns estimated in Section 3. Using the daily municipality-level telework shares, we quantify how telework reshapes spending through two opposing channels: the positive demand shock from increased presence at home and the negative shock from reduced presence at workplaces. To estimate these effects, we estimate a Poisson regression with two-way fixed effects using a Pseudo-Maximum Likelihood method (PPML), controlling for confounding factors such as weather, transport disruptions, and part-time worker patterns. This framework allows us to estimate the semi-elasticity of local consumption with respect to telework intensity and to quantify its aggregate impact by aggregating municipality-level differences between observed outcomes and a model-implied no-telework benchmark, while uncovering spatial and sectoral heterogeneity in how telework redistributes economic activity across the Lyon metropolitan area.

4.1 Empirical Framework for Causal Identification

Model specification. To identify the causal effects of telework on in-store spending, our strategy exploits the systematic within-municipality variation in telework practices across weekdays, as well as structural differences in telework exposure across municipalities. Municipality fixed effects absorb all time-invariant differences in consumption levels across locations, while day-of-week fixed effects capture common temporal patterns in spending. Under the assumption that, conditional on these fixed effects and observable controls, the within-week timing of telework is orthogonal to unobserved municipality-specific consumption shocks, this strategy supports a causal interpretation of the estimated telework effects.

We explicitly identify the two opposing demand shocks generated by telework—a positive shock from increased presence at home and a negative shock from reduced presence at the workplace—using two indicators that measure, respectively, the telework-induced shares of workers present in their municipality of residence and absent from their municipality of work. Distinguishing these two margins is crucial, as focusing on only one dimension would mechanically confound relocation effects with net changes in local consumption. By jointly modeling both channels, we can isolate the redistribution of spending across space from changes in daily spending, and thereby infer the net combined effect of telework on local consumption at the municipality level and overall the Lyon FUA.

The core specification takes the form of a Poisson regression with two-way fixed effects:

$$Y_{it} = \exp\left[\theta_1 \mathrm{RT}_{it}^{(\mathcal{H})} + \theta_2 \mathrm{RT}_{it}^{(\mathcal{W})} + \sum_c \eta_c X_{it}^c + \delta_i + \gamma_{gt} + \epsilon_{it}\right], \tag{4}$$

where the dependent variable Y_{it} denotes the number or total value of in-person transactions for municipality i on date t; the main explanatory variables are $\mathrm{RT}_{it}^{(\mathcal{H})}$, which denotes the estimated share of employed residents working from home in municipality i on date t, and $\mathrm{RT}_{it}^{(\mathcal{W})}$, which captures the share of workers absent from their workplace due to telework. A set of control variables, $\sum_c X_{it}^c$, is included, such as the share of part-time workers present at home or absent from the workplace, rainfall (Meteo France), and public transport disruptions (traffic alerts from the Lyon public transport system, TCL Twitter account), as these factors are likely correlated with both patterns in consumption and telework practice. Municipality fixed effects δ_i control for time-invariant local characteristics that shape transaction levels and values independently of daily telework variation, such as local economic structure, retail density, or transport accessibility. Date-by-area-type fixed effects γ_{gt} absorb daily shocks and capture temporal dynamics specific to different types of municipalities. Area types are defined in four classes—(1) Lyon city, (2) the rest of the urban core, and two categories within the surrounding commuting zone: (3) urban and (4) rural—based on the municipal density grid developed by Insee (Beck et al., 2022). This specification mitigates concerns that differences in weekday consumption patterns across municipalities—arising, for example, from socio-economic composition or from systematic differences between commerce- and service-dense areas versus less dense areas—could bias our estimates. In practice, it ensures that the identification of telework effects comes from deviations in telework intensity within a municipality relative to the expected pattern for its area type on a given day, rather than from daily differences in spending behavior across municipalities unrelated to telework.

The coefficients θ_1 and θ_2 represent the semi-elasticities of daily in-shop spending with respect to the telework indicators. Given that these variables are expressed in percentage points, ranging from 0 to 1, a one-percentage-point increase corresponds to a one-unit increase in the model. The associated effect on spending is interpreted as $(\exp(\theta \times 0.01) - 1) \times 100\% \approx \theta$, that is, the percentage change in the outcome for a one-percentage-point increase in the telework share. We expect θ_1 to be positive, indicating that telework-induced presence at home increases local consumption. Conversely, we expect θ_2 to be negative, indicating that telework-induced absence from the workplace reduces local consumption.

The model is estimated using a Poisson Pseudo-Maximum Likelihood (PPML) method, which is particularly well suited to our setting where the dependent variables consist of transaction counts and values. PPML naturally accommodates zero outcomes and yields consistent estimates in the presence of heteroskedasticity, as shown by Silva and Tenreyro (2006). Standard errors are clustered at the municipality level to account for serial correlation and unobserved shocks common within municipalities over time. Baseline results are reported in Table 2.

Work-to-home consumption substitution rate. To summarize the relative magnitude of the two opposing effects of telework on weekdays, we define a stylized work-to-home consumption substitution rate as the ratio of the estimated marginal effects: $|\theta_1/\theta_2|$.[13]

For small changes in telework rates, $|\theta_1/\theta_2|$ indicates the relative strength of consumption gains associated with increased telepresence at home versus consumption reductions associated with workplace absence. A value close to 1 suggests that residential and workplace telework have roughly comparable marginal impacts on local spending, while values below 1 indicate that home presence has a weaker effect than workplace absence, and values above 1 indicate the opposite. Estimated substitution rates for each specification are reported in Table 2.

Later, in the robustness section, we address an empirical discrepancy in variability between residential and workplace telework shares—their denominators differ and residential shares fluctuate more across weekdays—which could influence the estimated substitution rate. By standardizing both variables and re-estimating the model, we find results broadly consistent with the baseline, indicating that this differential variability does not materially affect our conclusions (see Section C.2.2).

Local net effect. To assess the overall impact of telework on consumption, we leverage the estimated marginal effects of telework-induced presence at home and absence from the workplace. Our analysis begins at the municipality level, where we determine which of the two opposing demand shocks, the positive effect of home-based consumption or the negative effect of workplace-based consumption, prevails locally. For each municipality i, we compute the predicted percentage change in transactions as the sum of these two effects, weighted by the corresponding average municipal telework shares.

Formally, the average daily predicted impact of telework is given by:

$$\begin{aligned}\Delta_i\% &= \frac{100}{T}\sum_t (\widehat{y}_{it} - \widehat{y}^0_{it})/\widehat{y}^0_{it} \\ &= \frac{100}{T}\sum_t \Big(\exp(\widehat{\theta}_1 \mathrm{RT}^{(\mathcal{H})}_{it} + \widehat{\theta}_2 \mathrm{RT}^{(\mathcal{W})}_{it}) - 1 \Big)\end{aligned}$$

[13] Using Equation 4, the marginal effects of residential telepresence and workplace teleabsence on local consumption are $\frac{\partial Y}{\partial \mathrm{RT}^{(\mathcal{H})}} = \theta_1 Y$ and $\frac{\partial Y}{\partial \mathrm{RT}^{(\mathcal{W})}} = \theta_2 Y$. The ratio θ_1/θ_2 provides a stylized comparison of the relative responsiveness of consumption to residential versus workplace telework, without implying a direct one-to-one offset.

where $\widehat{y}_{it}$ denotes the predicted number or value of transactions of municipality i in date t from the PPML estimation of Equation 4, and $\widehat{y}^0_{it}$ denotes the corresponding predictions under a zero-telework scenario. The percentage difference between the two provides the net impact of telework.

This measure captures the net local demand effect of telework, showing how home- and workplace-based shifts in presence jointly translate into changes in local spending. By providing a spatially explicit perspective, it reveals which municipalities experience the most significant gains or losses due to changing work-location dynamics. The results are visualized in Figure 3. These effects are interpreted in a scenario where telework affects only the presence of workers at home or at the workplace, without altering the location of their residence or job, which appears to hold in European settings, as documented by the GIP POPSU Territoires (2022) in France and by Alipour et al. (2022) in Germany.

Aggregated net effect. To assess the overall daily impact of telework on consumption within Lyon Functional Urban Area, we aggregate the municipality-level effects estimated previously. Specifically, we weight each municipality's predicted percentage change in transactions due to telework, $\Delta_i\%$, by its average observed transaction level, and then sum across all municipalities. This approach yields the predicted total daily change in transactions across the territory attributable to telework.

Formally, the aggregate effect for the entire Lyon FUA is given by: $\Delta = \sum_i \Delta_i\% \times \frac{1}{T} \sum_t y_{it}$, where y_{it} denotes the observed number or value of transactions in municipality i and date t. his formulation captures the aggregate change in total transactions (in levels) induced by telework, weighting each municipality's estimated impact by its average observed transaction volume. We also express this aggregate change in percentage terms, relative to total observed spending across the FUA.

In addition, we compute this aggregate effect separately for different spatial groups within Lyon FUA: Lyon city, the rest of the urban core, urban municipalities in the commuting zone, and rural municipalities in the commuting zone. This disaggregation highlights the spatial heterogeneity in telework-induced consumption shifts, showing how the balance between home-based and workplace-based demand effects varies across the metropolitan hierarchy. Results are presented in Table 3.

4.2 Baseline Results: Asymmetric Demand Shocks and Substitution Rates

4.2.1 Marginal Effects of Telework on Local Consumption

Table 2 reports the estimates from Equation 4, with daily transaction count and value as dependent variables, respectively. Column 1 presents the baseline specification. Column 2 introduces controls for the share of part-time workers on their day off accounting for their presence at home and absence from their workplace. Columns 3 and 4 introduce weather-related controls: a rain dummy and rain intensity categories, respectively. Column 5 includes a dummy for public transport disruption (bus, tram, metro), while column 6 adds interactions between these disruptions and telework shares. Finally, column 7 incorporates the full set of controls, which is our preferred specification, although including these controls does not substantially alter the main coefficients, supporting their robustness.

Result 1. Telework increases home consumption and reduces workplace consumption on weekdays. The results reveal a consistent and statistically significant pattern across all specifications.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Transaction count							
$RT^{(\mathcal{H})}$	1.147***	0.984***	1.150***	1.151***	1.146***	1.024***	0.985***
	(0.226)	(0.217)	(0.223)	(0.223)	(0.224)	(0.227)	(0.213)
$RT^{(\mathcal{W})}$	-1.736***	-1.738***	-1.717***	-1.720***	-1.732***	-1.668***	-1.713***
	(0.383)	(0.377)	(0.376)	(0.375)	(0.386)	(0.389)	(0.372)
$PT^{(\mathcal{H})}$		1.663*					1.665*
		(0.978)					(0.967)
$PT^{(\mathcal{W})}$		1.473**					1.490**
		(0.749)					(0.746)
Rain			-0.008*				-0.009**
			(0.004)				(0.004)
Light rain				-0.008*			
				(0.004)			
Moderate rain				-0.014			
				(0.010)			
Public transp. disrupt.					0.009	-0.006	0.008
					(0.007)	(0.014)	(0.007)
$RT^{(\mathcal{H})}$ × Public transp. disrupt.						0.720	
						(0.444)	
Public transp. disrupt. × $RT^{(\mathcal{W})}$						-0.641	
						(0.453)	
Fit statistics							
Observations	10,640	10,640	10,640	10,640	10,640	10,640	10,640
BIC	166,692.0	166,326.0	166,657.1	166,662.6	166,645.0	166,472.2	166,239.7
Inferred work-to-home consumption substitution rate							
$\lvert\frac{\theta_1}{\theta_2}\rvert$	0.661***	0.566***	0.670***	0.669***	0.661***	0.614***	0.575***
	(0.147)	(0.132)	(0.147)	(0.146)	(0.147)	(0.146)	(0.132)
Panel B: Transaction value							
$RT^{(\mathcal{H})}$	1.064***	0.966***	1.066***	1.067***	1.064***	0.980***	0.969***
	(0.269)	(0.281)	(0.266)	(0.266)	(0.270)	(0.289)	(0.279)
$RT^{(\mathcal{W})}$	-1.363***	-1.359***	-1.350***	-1.353***	-1.363***	-1.288***	-1.343***
	(0.391)	(0.402)	(0.387)	(0.386)	(0.393)	(0.389)	(0.401)
$PT^{(\mathcal{H})}$		0.838					0.849
		(0.968)					(0.964)
$PT^{(\mathcal{W})}$		2.919***					2.934***
		(0.764)					(0.763)
Rain			-0.006				-0.007
			(0.005)				(0.005)
Light rain				-0.006			
				(0.005)			
Moderate rain				-0.012			
				(0.012)			
Public transp. disrupt.					0.006	0.007	0.006
					(0.008)	(0.016)	(0.008)
$RT^{(\mathcal{H})}$ × Public transp. disrupt.						0.700**	
						(0.345)	
Public transp. disrupt. × $RT^{(\mathcal{W})}$						-0.742**	
						(0.362)	
Fit statistics							
Observations	10,640	10,640	10,640	10,640	10,640	10,640	10,640
BIC	5,434,199	5,407,037	5,433,320	5,433,133	5,433,321	5,428,426	5,404,987
Inferred work-to-home consumption substitution rate							
$\lvert\frac{\theta_1}{\theta_2}\rvert$	0.780***	0.711***	0.790***	0.788***	0.781***	0.761***	0.721***
	(0.196)	(0.195)	(0.197)	(0.196)	(0.197)	(0.207)	(0.197)

Note: Signif. codes: ***: 0.01, **: 0.05, *: 0.1. Clustered standard-errors at the municipality level in parentheses. All specifications include municipality and date-by-zone type fixed effects. Standard errors of the inferred work-to-home consumption substitution rate, $\lvert\frac{\theta_1}{\theta_2}\rvert$, are computed using the Delta Method.

Table 2: Effects of Telework on Transaction Counts (Panel A) and Values (Panel B)

A one percentage-point increase in the share of resident workers working from home is associated with a 1% increase in local transaction count (column 7, significant at the 1% level). Conversely, a one percentage-point increase in the share of workers absent from their workplace due to telework corresponds to a 1.7% decrease in transaction counts and a 1.3% decrease in transaction values. These asymmetric effects highlight how telework simultaneously stimulates and suppresses local economic activity, with the negative workplace shock outweighing the positive residential shock.

Result 2. Telework partially shifts workplace spending to home. The inferred work-to-home consumption substitution rates, reported at the bottom of Table 2, summarize the relative strength of the two opposing demand shocks generated by telework. In our preferred specification, the ratio of the estimated marginal effects is 0.57 for transaction counts and 0.72 for transaction values, indicating that the positive effect for one-percentage-point increase presence at home compensates for only part of the negative effect of one-percentage-point increase in workplace absence. The higher rate for transaction values suggests that the monetary volume of spending is somewhat better preserved than the number of transactions, reflecting differences in the size and nature of purchases between home- and workplace-associated consumption.

To account for the nonlinearity in the substitution rates, we compute their standard errors using the Delta Method (Pierce, 1982), enabling rigorous inference about the degree of consumption reallocation. For transaction values, the 95% confidence interval of [0.335, 1.107] spans the value of 1, indicating substantial heterogeneity across municipalities. In some cases, residential consumption gains may fully or even over-compensate for workplace losses, while in others, the net effect remains negative. This heterogeneity underscores the importance of disaggregated analysis to understand the localized impacts of telework.

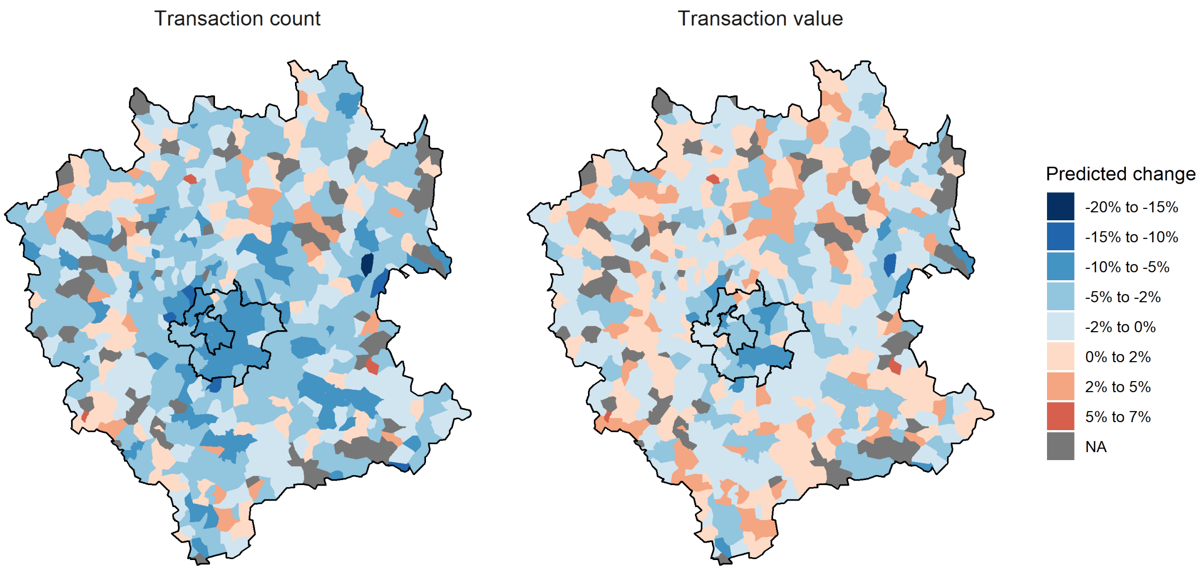
4.2.2 Net Effects of Telework on Local and Aggregate Consumption

We now analyze the net local and aggregate effects of telework. The first allows us to assess how telework reshapes the spatial distribution of consumption across the functional urban area, while the second measures its net impact on overall consumption.

Result 3. Telework leads to a spatial redistribution of consumption from the urban core to the commuting zone. Figure 3 maps the estimated average daily net effect of telework on transaction activity across all municipalities in the Lyon Functional Urban Area. The results reveal pronounced spatial heterogeneity, with demand gains concentrated in the commuting zone and losses predominant in the urban core.

Overall, 81% of municipalities within the Lyon FUA experience a decline in transaction counts relative to a zero-telework scenario on weekdays, while 60% show a decline in transaction values. The urban core records the largest losses, particularly in Lyon city, where transaction counts drop by 6.8% and values by 3%. In contrast, a subset of municipalities, primarily residential areas in the commuting zone, benefit from increased spending, illustrating how telework reshapes the economic geography of the region.[14]

[14] Figure 21 in Appendix C.3 examines how predicted consumption changes relate to municipalities' demographic characteristics. The left-hand figures show that municipalities with a higher ratio of resident teleworkers to employed teleworkers experience larger predicted transaction changes, even turning positive in some cases due to asymmetric demand shocks. Municipalities with a larger resident population relative to their workforce also exhibit stronger positive effects. Additionally, Figures 16-20 illustrate how these effects vary throughout the week, highlighting that telework's impact on consumption is both spatially uneven and temporally dynamic, reflecting daily telework patterns.



Note: The two figures show the average daily effect of telework on transaction counts and transaction values, respectively. This is computed as the daily average of the ratio $(\widehat{y}_{it} - \widehat{y}^0_{it})/\widehat{y}^0_{it}$, where $\widehat{y}_{it}$ denotes the model-predicted values for municipality i at date t, and $\widehat{y}^0_{it}$ denotes the corresponding predicted values under a zero-telework scenario. Predictions are obtained from our preferred specification, that includes municipality fixed effects, date-by-zone-type fixed effects, and the full set of control variables.

Figure 3: Predicted Daily Change in Transaction Counts and Values Across the Lyon FUA

Result 4. Telework leads to a net reduction in transactions. Table 3 aggregates these effects across the four spatial areas within the Lyon FUA. The estimated aggregate impact of telework is consistently negative across all zone groups, though the magnitude of the reduction increases with urban centrality. Lyon city exhibits the largest decrease in transaction counts, with a 6.8% decline, followed by the rest of the urban core at 6.7%. The urban commuting zone shows a smaller reduction of 4.8%, while the rural commuting zone is the least affected, with a decline of only 2.7%. In terms of transaction values, the rest of the urban core shows a slightly larger percentage decrease than Lyon city (3.3% versus 3%), though in absolute terms, the per-municipality change is largest in Lyon city. Overall, the Lyon FUA experiences a 5.8% decline in daily transaction counts and a 2.6% decrease in daily transaction value, equivalent to a reduction of €683,000 in total spending.

These findings underscore the uneven distribution of telework's economic consequences. While the aggregate effect is negative, some municipalities, particularly those with a more residential profile, experience gains. This spatial redistribution of consumption from the urban core to the commuting zone reflects the asymmetric intensity of the two demand shocks: workplace absences are more concentrated in central areas, where teleworkable jobs are densely located, while residential gains are more dispersed.

Zone group	(1) N_g	Transaction count (2) $\sum_g y_{ig}$	(3) $\Delta_g\%$	(4) Δ_g	Transaction value (5) $\sum_g y_{ig}$	(6) $\Delta_g\%$	(7) Δ_g€
Lyon city	9	227,074	-6.82	-15,497	6,195,465	-2.98	-184,758
Rest of the core	30	190,564	-6.67	-12,713	6,944,555	-3.30	-229,428
Urban commuting zone	166	254,930	-4.82	-12,285	10,467,588	-2.39	-250,169
Rural commuting zone	327	58,652	-2.70	-1,584	2,331,438	-0.81	-18,803
All	532	731,220	-5.75	-42,079	25,939,046	-2.63	-683,158

Note: Column 1 reports the number of municipalities in each group. Column 2 gives the total daily number of transactions over all municipalies within each group. Column 3 presents the estimated aggregate percentage change in transaction counts attributable to telework, and Column 4 shows the corresponding change in transaction counts per day. Column 5 reports the total daily value of transactions within each group. Column 6 presents the estimated aggregate percentage change in transaction values attributable to telework, and Column 7 shows the corresponding change in transaction values per day.

Table 3: Aggregate Impact of Telework: Predicted Percentage Change in Transactions by Spatial Zone

4.3 Sectoral Heterogeneity in Telework's Consumption Effects

The aggregate results mask substantial variation in how different sectors respond to telework-induced shifts in consumer presence. To explore this heterogeneity, we disaggregate total transactions into seven key retail and service categories: *Restaurants*, (2) *Food Retail*, (3) *Bars and Drinks*, (4) *General Retail*, (5) *Clothing and Beauty Retail*, (6) *Sports and Recreation*, and (7) *Health and Wellness Retail*. Sector definitions are constructed based on merchant activity classifications (APE codes, "Activité Principale Exercée"), which are aggregated into economically meaningful groups. The correspondence between APE codes, their descriptions, and the aggregated sector categories is detailed in Appendix C.1 in Table 12.

4.3.1 Marginal Effects of Telework on Local Consumption by Sector

Table 4 presents the estimated effects of telework on transaction counts and values for each sector. The results highlight notable differences in sectoral sensitivity to telework-induced demand shocks.

Result 5. Telework drives sector-specific shifts: restaurant transactions decline, bars and food retail transactions increase. Routine-related sectors, such as Restaurants, Food Retail, and Bars and Drinks, exhibit the strongest and most significant effects, both in transaction counts and values. The positive and negative demand shocks resulting from telework-induced shifts in presence are asymmetric, with some sectors experiencing net reductions and others net gains.

Restaurants are the sector most adversely affected by telework-induced workplace absence. Our estimates reveal that a one percentage-point increase in the realized telework share at the workplace corresponds to a 4.2% decline in transaction counts and a 3.9% reduction in transaction values. These effects translate into work-to-home substitution rates of just 0.27 for transaction counts and 0.34 for transaction values, meaning that only 27-34% of the spending lost at workplace restaurants is recaptured through increased residential consumption. This stark imbalance underscores the sector's heavy reliance on workplace foot traffic, a demand driver that telework

	Restaurants (1)	Food (2)	Bars (3)	General (4)	Clothing (5)	Recreation (6)	Health (7)
Panel A: Transaction count							
$RT^{(\mathcal{H})}$	1.124***	1.233***	3.390***	0.9146*	0.3812	3.426	0.2259
	(0.422)	(0.226)	(1.20)	(0.482)	(0.773)	(3.21)	(0.257)
$RT^{(\mathcal{W})}$	-4.184***	-1.515***	-2.395	-1.220**	-0.711	-5.649	-0.626*
	(0.781)	(0.416)	(1.63)	(0.593)	(0.966)	(4.05)	(0.357)
Fit statistics							
Observations	9,200	7,140	4,340	5,300	2,640	3,320	4,880
BIC	103,928.4	117,787.2	54,097.8	64,009.5	31,714.6	38,846.6	39,287.8
Inferred work-to-home consumption substitution rate							
$\lvert\frac{\theta_1}{\theta_2}\rvert$	0.269***	0.814***	1.416*	0.749**	0.536	0.607*	0.361
	(0.090)	(0.191)	(0.804)	(0.345)	(0.732)	(0.378)	(0.313)
Panel B: Transaction value							
$RT^{(\mathcal{H})}$	1.323**	1.543***	3.625***	0.3792	-0.2373	2.926	0.4205
	(0.628)	(0.326)	(1.24)	(0.574)	(0.835)	(1.87)	(0.374)
$RT^{(\mathcal{W})}$	-3.931***	-1.334*	-2.526	-0.987*	-0.297	-5.668**	-0.809
	(0.972)	(0.683)	(1.60)	(0.545)	(0.874)	(2.65)	(0.653)
Fit statistics							
Observations	9,200	7,140	4,340	5,300	2,640	3,320	4,880
BIC	2,308,510.0	2,552,940.9	933,548.1	2,583,980.8	1,501,635.4	1,099,998.1	528,080.4
Inferred work-to-home consumption substitution rate							
$\lvert\frac{\theta_1}{\theta_2}\rvert$	0.337***	1.156**	1.435**	0.384	0.800	0.516*	0.520
	(0.120)	(0.552)	(0.767)	(0.49)	(4.757)	(0.28)	(0.422)

Note: Signif. codes: ***: 0.01, **: 0.05, *: 0.1. Clustered standard-errors at the municipality level in parentheses. All specifications include the whole set of controls (as in column 7 of Table 2), as well as municipality and date-by-zone type fixed effects. Standard errors of the inferred work-to-home consumption substitution rate, $\lvert\frac{\theta_1}{\theta_2}\rvert$, are computed using the Delta Method.

Table 4: Sector-Specific Telework Effects on Transaction Counts (Panel A) and Values (Panel B)

cannot easily replicate. Unlike grocery shopping or leisure activities, which can be shifted to residential neighborhoods, restaurant visits are inherently tied to workplace proximity, making this sector particularly vulnerable to the spatial redistribution of consumption caused by telework.

In contrast, Bars and Drinks respond positively to residential demand, with substitution rates exceeding 1 for both transaction counts (1.42) and values (1.44). This suggests that increased at-home or local leisure consumption more than offsets reductions in workplace-based activity, likely due to teleworkers shifting their social and recreational spending toward residential neighborhoods. Food Retail also responds positively to telework, though more symmetrically. While transaction counts decline slightly on weekdays, transaction values rise, consistent with larger grocery purchases for home-cooked meals and the time savings from reduced commuting. This pattern aligns with intertemporal substitution, explored further in Section 5.2.

Other sectors, such as General Retail, Clothing, Recreation, and Health services, show weaker or statistically insignificant responses, reflecting lower dependence on weekday routines. Overall, telework reshapes consumption patterns: sectors tied to office presence face reductions, whereas those with substitutable at-home demand, especially food retail and beverage services, experience gains.

4.3.2 Net Effects of Telework on Local and Aggregate Consumption by Sector

We now examine the aggregate sectoral impacts of telework, synthesizing results across the four spatial zones to assess its overall economic impact on local consumption. Table 5 consolidates these effects, quantifying the magnitude of telework's impact by sector.

Result 6. Aggregate telework effects on daily transaction value: restaurants decline by 21%, bars increase by 15%, food retail rises 3%. Restaurants experience the largest reductions, with counts falling up to 28% in Lyon city and values declining by up to 24%, with effects diminishing in outer zones. Food Retail sees minor declines in counts (-2% to 0%) but modest increases in values (2% to 4%), indicating larger, less frequent purchases. General Retail experiences moderate decreases in central zones, though far smaller than for Restaurants. Bars and Drinks show substantial positive effects, especially in Lyon (+18% in counts, +19% in values), reflecting substitution toward leisure-oriented spending. These patterns illustrate that telework not only redistributes consumption spatially but also affects sectors differently depending on their sensitivity to workplace presence and potential for at-home substitution.[15]

4.4 Robustness Checks and Sensitivity Analyses

To ensure the reliability and validity of our empirical findings, we implement a comprehensive battery of robustness checks and sensitivity analyses, fully documented in Appendix C.2. These analyses serve three key purposes. First, we verify our results' stability against potential biases through examinations of multicollinearity, omitted variable bias, and model specifications. Second, we explore how results respond to alternative assumptions through sensitivity analyses assessing measurement errors, alternative telework definitions, and different model specifications. Finally, we employ advanced identification strategies to strengthen causal inference and test result sensitivity to different approaches. These analyses collectively show that our findings reflect genuine causal relationships between telework and local consumption, not spurious correlations or model misspecification.

Robustness checks. We first focus on robustness checks that examine the stability of our core results against potential biases. We begin with rigorous diagnostic tests for multicollinearity using condition numbers of the Hessian matrix, which reveal values substantially below the problematic threshold of 30 (ranging from 4 to 15 across specifications), providing strong evidence against significant linear dependencies among our regressors. To address a more subtle identification challenge, we construct alternative telework measures that explicitly exclude workers

[15] Telework's sectoral impacts also reveal pronounced spatial heterogeneity, particularly within Lyon's urban core (see Figures 23-26 in Appendix C.4.2). Restaurants experience the most significant declines in transactions, with the steepest reductions concentrated in the urban core and its immediate surroundings. For food retail, transaction values generally increase, but a clear spatial divide emerges: western areas of the urban core, where more teleworkers reside, see gains, while eastern areas show smaller increases or even declines. General retail suffers losses in the urban core and across the broader metropolitan area, though the commuting zone sees slightly more transactions but lower overall values. Bars and drinks stand out with substantial increases in both transaction counts and values across the entire metropolitan area, with western areas again benefiting more than eastern ones. The distribution of predicted transaction changes further highlights these patterns (see Figure 27): restaurants show a skewed distribution toward negative changes, indicating widespread declines. Food retail's distribution centers near zero for transaction counts but skews positively for values, reflecting larger but less frequent purchases. Bars and drinks exhibit a broad distribution of gains, with significant variability across municipalities. General retail's distribution centers around zero for transaction values but skews negatively for counts, signaling moderate reductions in some areas. These patterns underscore the uneven geographic and sectoral impacts of telework.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Transaction count			Transaction value		
	N_g	$\sum_{i \in g} y_{ig}$	Δ_g %	Δ_g	$\sum_{i \in g} y_{ig}$	Δ_g %	Δ_g €
Restaurants							
Lyon city	9	68,955	-27.87	-19,221	1,481,482	-24.07	-356,556
Rest of the core	30	36,113	-25.93	-9,366	752,095	-22.06	-165,924
Urban commuting zone	144	35,712	-19.80	-7,072	912,920	-16.91	-154,396
Rural commuting zone	277	8,900	-13.68	-1,218	278,466	-10.76	-29,967
All	460	149,680	-24.64	-36,876	3,424,964	-20.64	-706,844
Food Retail							
Lyon city	9	86,739	-1.83	-1,587	1,719,538	4.19	71,994
Rest of the core	30	88,447	-2.30	-2,031	2,774,655	2.79	77,348
Urban commuting zone	139	122,539	-1.50	-1,835	4,561,443	2.18	99,543
Rural commuting zone	179	29,187	-0.03	-9	1,073,417	3.15	33,859
All	357	326,912	-1.67	-5,462	10,129,054	2.79	282,744
General Retail							
Lyon city	9	23,486	-2.09	-491	899,850	-6.19	-55,712
Rest of the core	30	23,424	-3.13	-732	1,370,675	-5.91	-81,037
Urban commuting zone	113	42,235	-2.12	-895	2,229,353	-4.38	-97,706
Rural commuting zone	113	6,738	-0.53	-35	294,973	-2.89	-8,536
All	265	95,884	-2.25	-2,154	4,794,850	-5.07	-242,990
Bars and Drinks							
Lyon city	9	13,824	17.56	2,427	250,043	19.43	48,571
Rest of the core	23	3,736	12.01	449	83,171	13.26	11,028
Urban commuting zone	93	5,310	8.81	468	130,821	10.14	13,260
Rural commuting zone	92	2,354	12.86	303	64,460	13.94	8,983
All	217	25,222	14.46	3,646	528,495	15.49	81,842

Note: Column 1 reports the number of municipalities in each group. Column 2 gives the total daily number of transactions over all municipalities within each group. Column 3 presents the estimated aggregate percentage change in transaction counts attributable to telework, and Column 4 shows the corresponding change in transaction counts per day. Column 5 reports the total daily value of transactions over all municipalities within each group. Column 6 presents the estimated aggregate percentage change in transaction values attributable to telework, and Column 7 shows the corresponding change in transaction values per day.

Table 5: Net Sectoral Impact of Telework on Transaction Counts and Values by Sector and Spatial Zone

who both reside and work in the same municipality (representing 12.9% of potential teleworkers), thereby eliminating any risk of double-counting bias. The exceptional stability of coefficients in our telecommuter-specific models (Table 13) supports that our findings are not artifacts of measurement construction. We further strengthen our identification by incorporating critical control variables that could simultaneously affect telework patterns and consumption outcomes. Our analysis accounts for part-time workers' day-off patterns, which significantly increase local consumption when these workers are present in their residential areas. We also control for weather conditions, finding that rain reduces transactions by about 1%, and public transport disruptions, which while not directly affecting consumption levels, appear to moderate the impact of telework on local spending. Specifically, they interact with telework shares to slightly amplify the positive effects of residential presence and the negative effects of workplace absence. Although these interaction effects are not statistically significant, their direction is consistent with the idea that transport disruptions reinforce the spatial reallocation of consumption: when commuting is more difficult, spending tends to shift toward neighborhoods where workers are present (home) and away from workplaces.

Sensitivity analyses. Second, we present extensive sensitivity analyses that systematically evaluate how our results respond to alternative assumptions and measurement specifications. We first implement a standardization approach to address the asymmetry in variation patterns between residential and workplace telework shares, rescaling each variable to have a mean of zero and a standard deviation of one. This ensures that the estimated effects are directly comparable, controlling for the fact that residential telework typically fluctuates more across weekdays than workplace telework. The results in Table 15 show consistent substitution rates (0.64-0.80) that confirm our core conclusion that most municipalities experience net losses in local spending due to telework, even after accounting for differential variability in our measures. A more rigorous measurement error analysis uses controlled simulations where we intentionally introduce varying levels of normally distributed noise into our telework variables. Figure 12 demonstrates the expected attenuation pattern where higher measurement error brings coefficients closer to zero, yet all estimates maintain their theoretical signs and statistical significance even at the highest error level. This systematic attenuation suggests our baseline estimates represent conservative lower bounds, as measurement error tends to bias estimates toward zero rather than inflate them. We further test alternative measurement approaches that exploit different sources of variation. The spatial heterogeneity analysis uses zone-specific telework propensities (Table 16), while another approach employs finer geographic resolution measures (method described in Section E, results in Table 17). Both approaches yield qualitatively consistent results with our main findings, though with appropriately larger standard errors reflecting the additional measurement noise. The consistency across these alternative specifications provides compelling evidence that our results are not sensitive to the specific operationalization of our telework variables.

Causal identification strategies. Third, we implement causal identification strategies to strengthen the causal interpretation of our findings. Our most sophisticated approach uses a shift-share instrumental variable (IV) design, detailed in Appendix C.2.3, which combines pre-COVID telework propensities by occupation with daily deviations from baseline day-off patterns among executive part-time workers. This instrument leverages plausibly exogenous variation in telework: the pre-pandemic occupational distribution of teleworkable jobs is unlikely to be correlated with daily consumption shocks in 2022, while the daily deviations—which largely reflect that the actual average number of teleworked days among teleworkers exceeds the average weekly days off of executive part-time workers—capture unanticipated shifts in home presence that are plausibly orthogonal to local spending decisions. The IV results in Tables 18–20 confirm our core findings while accounting for potential endogeneity, with substitution rates slightly lower than but substantively similar to our baseline estimates. The stability of results across different instrument years (1999, 2010, 2015) as shown in Figures 13 and 14 provides additional confidence in our causal interpretations. Following recent guidance on shift-share instruments (Borusyak et al., 2025), we also assess the plausibility of the exclusion restriction (see redundancy tests in columns 7 and 10): the instruments appear to influence local consumption solely through their effect on telework. We complement this with an alternative identification strategy that relies solely on spatial variation in telework potential across municipalities (Table 21). While this approach yields less precise estimates due to the cross-sectional nature of the variation, the directional consistency with our main results provides additional confirmation of our findings' robustness. The coefficients for residential and workplace telework potential maintain their expected signs and significance, though with larger standard errors that reflect the trade-off between precision and robustness when using spatial rather than temporal variation.

5 Beyond the Baseline: Model Extensions

This section extends the analysis of telework's impact on local consumption by examining two critical dimensions largely overlooked in prior literature: spatial spillovers and intertemporal substitution. This section quantifies these dynamics, first by modeling how telework in one municipality affects spending in adjacent areas, and second by assessing whether telework shifts consumption from weekends to weekdays. These analyses reveal how telework's economic footprint extends beyond immediate residential and workplace locations, offering a more complete picture of its role in reshaping urban consumption patterns.

5.1 Spatial Spillovers: How Telework Redistributes Consumption Across Municipalities

The effects of telework may not be confined to the municipalities where teleworkers live or work. Instead, teleworkers' increased flexibility and saved commuting time could lead them to spend in neighboring areas, generating spatial spillovers that further redistribute economic activity across the metropolitan area.

To capture spatial spillover effects, we extend the baseline model to include the influence of telework in neighboring municipalities:

$$Y_{it} = \exp\left[\theta_1 \mathrm{RT}_{it}^{(H)} + \theta_2 \mathrm{RT}_{it}^{(W)} + \lambda_1 \sum_{j \neq i} w_{ij} \mathrm{RT}_{jt}^{(H)} + \lambda_2 \sum_{j \neq i} w_{ij} \mathrm{RT}_{jt}^{(W)} + \delta_i + \gamma_{gt} + \epsilon_{it}\right] \tag{5}$$

where $\sum_{j \neq i} w_{ij} \mathrm{RT}_{jt}^{(\cdot)}$ represents the spatially weighted telework share in municipalities neighboring i. Proximity is defined using a contiguity-based spatial weight matrix wij, where $w_{ij} > 0$ if i and j share a boundary and $w_{ij} = 0$ otherwise. The weights are row-standardized so that each row sums to 1, which allows these spatial lags to be interpreted as the average telework intensity in neighboring areas. Including these terms captures the extent to which telework in nearby municipalities affects local outcomes through inter-municipal mobility.[16] The estimation results for model 5 are presented in Table 6.

Result 7. Telework generates spatial spillovers through worker mobility: neighboring municipalities gain from home-based presence and lose from workplace absence. The estimation results of model 5, reported in Table 6, provide evidence of both direct and spatial spillover effects of telework on local consumption activity. We find significant effects of telework shares in neighboring municipalities on transactions' count and value. A one-percentage-point increase in telework-induced presence at home in neighboring areas, $\mathrm{RT}_{\text{neighbors}}^{(\mathcal{H})}$, is associated with a 1.1% increase in both transaction counts and values. This effect is even larger than the direct one. This pattern

[16]We do not model spatial correlation in the error terms, as no available R package currently supports spatial model estimation combining a Poisson-distributed dependent variable with two-way fixed effects. This extension is deferred to future research.

suggests that residents of adjacent municipalities may be mobile on telework days, generating additional consumption outside their own municipality of residence. Conversely, a one-percentage-point increase in telework rates at workplaces in neighboring municipalities, $\mathrm{RT}^{(\mathcal{W})}_{\text{neighbors}}$, is associated with a 1.1% decrease in local transactions, possibly because teleworkers, when on-site, consume as well in surrounding municipalities as part of their trip chain. Hence, reduced teleworkers inflows negatively affect surrounding areas, consistent with the findings of Miyauchi et al. (2025).

	Transaction count		Transaction value	
	(1)	(2)	(3)	(4)
$\mathrm{RT}^{(\mathcal{H})}$	1.006***	0.888***	0.865***	0.794***
	(0.264)	(0.244)	(0.259)	(0.270)
$\mathrm{RT}^{(\mathcal{W})}$	-1.616***	-1.525***	-1.311***	-1.271***
	(0.358)	(0.343)	(0.409)	(0.421)
$\mathrm{RT}^{(\mathcal{H})}_{\text{neighbors}}$	1.093**	1.021**	1.262***	1.145***
	(0.473)	(0.418)	(0.445)	(0.429)
$\mathrm{RT}^{(\mathcal{W})}_{\text{neighbors}}$	-1.132**	-1.312***	-1.077*	-1.056*
	(0.465)	(0.472)	(0.566)	(0.594)
$\mathrm{PT}^{(\mathcal{H})}$		2.006**		1.032
		(0.966)		(0.991)
$\mathrm{PT}^{(\mathcal{W})}$		1.308*		2.806***
		(0.734)		(0.748)
Rain		-0.008**		-0.006
		(0.004)		(0.005)
Public transp. disrupt.		0.008		0.005
		(0.007)		(0.008)
Fit statistics				
Observations	10,640	10,640	10,640	10,640
BIC	166,499.2	166,035.0	5,425,802.0	5,397,806.7

Note: Signif. codes: ***: 0.01, **: 0.05, *: 0.1. Clustered standard-errors at the municipality level in parentheses. All specifications include municipality and date-by-zone type fixed effects.

Table 6: Spatial Spillover Effects of Telework on Local Transaction Counts and Values

The coefficients associated with $\mathrm{RT}^{(\mathcal{H})}$ and $\mathrm{RT}^{(\mathcal{W})}$ remain largely stable after including neighborhing levels of telework, showing only a slight reduction in magnitude. Omitting the telework levels in neighboring municipalities does not lead to an overestimation of the direct effect. However, there is a notable indirect effect driven by inter-municipal mobility that must be taken into account. Accurately assessing the impact of telework therefore requires considering these mobility patterns: telework not only redistributes consumption between the municipality of residence and the workplace, but also generates significant spillover effects in other municipalities that teleworkers visit.[17]

[17] Significant spatial heterogeneity in telework's spillover effects across the Lyon Functional Urban Area (FUA) is also existing (see Table 23 in Appendix D.1). The direct positive effects of residential telepresence are statistically significant only in Lyon city and the rest of the urban core, whereas the negative effects of workplace absence are evident across all zones, with the strongest impacts observed in Lyon. Indirect effects from telepresence in neighboring municipalities are significant only for Lyon city, suggesting higher consumption mobility among its residents. Additionally, workplace absence in neighboring areas negatively affects both Lyon and the rest of the urban core, with Lyon experiencing the largest declines. These findings indicate that teleworkers with offices in the urban core often consume in surrounding areas when physically present at work, so reduced workplace attendance negatively impacts neighboring municipalities. This aligns with the trip-chaining behavior documented by Miyauchi et al. (2025). Notably, indirect spillover

5.2 Intertemporal Substitution: Shifts in Consumption Timing Between Weekdays and Weekends

In this section, we investigate whether telework alter the temporal allocation of consumption between weekdays and weekends. For instance, teleworkers might prepare meals at home during the week, when working from home, reducing weekday food-related expenditures while possibly increasing such spending on weekends during their grocery shopping. Alternatively, they may use the additional free time on telework days, due to the absence of commuting, to shift activities like grocery shopping from weekends to weekdays.

To investigate this intertemporal substitution channel, we use a subsample of cardholders for whom the billing address associated with online transactions is available. This information allows us to infer their likely municipality of residence. Using this subsample, we construct a matrix linking places of residence o (origins) to places of consumption d (destinations), aggregating both the number and the value of transactions.

To assess whether telework alters the timing of consumption, transactions are aggregated by cardholders' postcode of residence[18] and by date, irrespective of where they occur. The daily number and value of transactions are then regressed on the interaction between residents' telework shares and a weekend indicator, exploiting both cross-sectional variation in telework prevalence and day-to-day variation in consumption activity.

Specifically, we estimate the following PPML model, in which the dependent variable is the total daily number or value of daily transactions recorded by residents of a given postcode:

$$\begin{aligned} Y_{ot} = \exp \Big[& \sigma_1 \, \mathrm{TE}_o^{(\mathcal{H})} + \sigma_2 \, \mathrm{Weekend}_t + \sigma_3 \, \mathrm{TE}_o^{(\mathcal{H})} \times \mathrm{Weekend}_t \\ & + \sigma_4 \, \log(\mathrm{Population}_o) + \varepsilon_{ot} \Big] \end{aligned} \tag{6}$$

where the key explanatory variable is the interaction between the share of teleworkers among working residents, $\mathrm{TE}_o^{(\mathcal{H})}$, and a weekend indicator.

This model captures whether residents in areas with high telework prevalence tend to shift their overall consumption patterns temporally. A significant coefficient on the interaction term, $\mathrm{TE}_o^{(\mathcal{H})} \times \mathrm{Weekend}_t$, would support the hypothesis of intertemporal substitution driven by telework. A negative coefficient would indicate that teleworkers shift more of their consumption to weekdays, while a positive coefficient would suggest increased consumption on weekends. To account for unobserved heterogeneity across municipalities, we also estimate specifications including municipality fixed effects, which absorb all time-invariant characteristics of each area—such as average income, urban density, socio-economic composition or typical retail composition—that could otherwise confound the relationship between telework prevalence and spending patterns. This ensures that the estimated interaction effect reflects within-municipality temporal shifts in consumption rather than differences across municipalities. The estimation results for model 6 are reported in columns 1 and 2 of Table 7.

We further explore the intertemporal consumption effects of telework by distinguishing between transactions occurring at home (in the postcode of residence) and those away, by aggregating transactions in destination different from home all together. This model enables us to capture

effects are often comparable to, or even exceed, direct effects, likely due to the prevalence of trip chaining in dense commuting areas.

[18] Postcodes are larger geographical units than municipalities: a single postcode may cover between one and eighteen municipalities, with an average of five.

not only the overall effect of telework and weekends on consumption but also how these effects differ between transactions made at home versus away from home.

$$
\begin{aligned}
Y_{odt} = \exp\Big[&\lambda_1 \, \mathrm{TE}_o^{(\mathcal{H})} + \lambda_2 \, \mathrm{Weekend}_t + \lambda_3 \, \mathrm{Home}_{od} \\
&+ \lambda_4 \, \mathrm{TE}_o^{(\mathcal{H})} \times \mathrm{Home}_{od} \\
&+ \lambda_5 \, \mathrm{Weekend}_t \times \mathrm{Home}_{od} \\
&+ \lambda_6 \, \mathrm{TE}_o^{(\mathcal{H})} \times \mathrm{Weekend}_t \\
&+ \lambda_7 \, \mathrm{TE}_o^{(\mathcal{H})} \times \mathrm{Weekend}_t \times \mathrm{Home}_{od} \\
&+ \lambda_8 \, \log(\mathrm{Population}_o) + \varepsilon_{odt}\Big] \qquad (7)
\end{aligned}
$$

where the variable Home_{od} is a dummy indicating whether the destination d matches the origin o (i.e., the transaction occurs within the cardholder's residential postcode). The interaction terms between telework intensity $\mathrm{TE}_o^{(\mathcal{H})}$, weekend status, $\mathrm{Weekend}_t$, and home location allow us to identify if teleworkers shift consumption specifically towards home during weekdays or weekends. A positive and significant coefficient λ_4 would indicate that telework increases consumption at home relative to other locations on weekdays. The triple interaction term λ_7 tests whether this home-focused shift differs on weekends compared to weekdays, revealing any intertemporal reallocation of consumption driven by telework.

From another perspective, λ_6 tests whether teleworkers substitute their outside-home consumption between weekend and weekdays, and the triple interaction term λ_7 tests whether this dynamic is different for home consumption. Again, to further control for unobserved heterogeneity, we estimate specifications with municipality fixed effects, which absorb all time-invariant characteristics of each area, and date fixed effects, which capture common shocks affecting all municipalities on a given day. The estimation results for model 7 are reported in columns 3 and 4 of Table 7.

Result 8. Telework induces intertemporal consumption shifts: weekend spending at home declines while weekday home transactions increase. Table 7 columns 1 and 2 presents estimates from the PPML regressions where the dependent variable is the number of daily transactions aggregated at the residential postcode level. The interaction term $\mathrm{TE}^{(\mathcal{H})} \times \mathrm{Weekend}$ captures whether the intensity of telework is associated with a redistribution of consumption toward or away from weekends. Across specifications, we find that this coefficient is negative and statistically significant, indicating that municipalities with higher telework intensity display lower weekend consumption. This suggests that telework enables individuals to shift part of their expenditures, such as grocery shopping or household-related purchases, from weekends to weekdays. These results support the intertemporal substitution mechanism through which telework reshapes not only the spatial allocation of consumption, but also its timing.

We further explore the intertemporal consumption effects of telework by distinguishing between transactions occurring in home postcode and those occurring elsewhere. The results in columns 3 and 4 in Table 7 reveal several key insights. First, consumers are significantly more likely to transact at home overall, as indicated by the large and highly significant coefficient on the Home indicator. Second, telework increases weekday consumption at home ($\mathrm{TE}^{(\mathcal{H})} \times \mathrm{Home}$), suggesting that individuals take advantage of their flexible schedules to shop locally during the

Dependent Variable:	Transaction count$_{ot}$		Transaction count$_{odt}$	
Model:	(1)	(2)	(3)	(4)
Variables				
$\text{TE}^{(\mathcal{H})}$	0.539		-11.8***	
	(1.12)		(0.510)	
Weekend	-0.048		0.000***	
	(0.031)		(0.000)	
log(Population)	1.210***		1.209***	
	(0.061)		(0.061)	
$\text{TE}^{(\mathcal{H})} \times$ Weekend	-0.339**	-0.330**	-0.0002***	-0.0001**
	(0.159)	(0.154)	(0.000)	(0.000)
Home			19.72***	23.04***
			(0.175)	(0.008)
$\text{TE}^{(\mathcal{H})} \times$ Home			12.39***	14.65***
			(0.874)	(0.041)
Weekend $\times$ Home			-0.049	-0.146***
			(0.031)	(0.030)
$\text{TE}^{(\mathcal{H})} \times$ Weekend $\times$ Home			-0.335**	-0.329**
			(0.159)	(0.154)
Fixed-effects				
Week	✓		✓	
Postcode o		✓		✓
Date		✓		✓
Fit statistics				
Observations	4,144	4,144	8,219	8,219
BIC	1,129,432.5	67,398.9	1,125,199.4	67,223.0

Note: Signif. codes: ***: 0.01, **: 0.05, *: 0.1. Clustered standard-errors at the postcode level in parentheses.

Table 7: Intertemporal consumption substitution induced by telework

workweek. Specifically, we find 15% more transactions in home postcode than outside for 1pp increase in teleworkers population share on weekdays. Third, weekend consumption at home is lower on average (Weekend $\times$ Home), and this reduction intensifies with higher levels of telework ($\text{TE}^{(\mathcal{H})} \times$ Weekend $\times$ Home). Specifically, for zero telework share, weekend consumption at home is 15% lower than in weekdays, and for 10pp telework share, we expect weekend consumption at home to be 17% lower than in weekdays. This pattern points to a form of intertemporal substitution: teleworkers shift part of their weekend consumption to weekdays, particularly in their residential areas. Notably, we find a significant zero effect of telework on weekend consumption away from home ($\text{TE}^{(\mathcal{H})} \times$ Weekend), underscoring that the observed substitution is specific to the home location.

6 Conclusion and Future Research

This paper investigates how telework (working from home) reshapes the spatial and temporal distribution of consumption within a metropolitan area by shifting individuals' daytime presence from workplaces to residences several days per week. It fills an important gap in the literature by jointly quantifying the two opposing effects of telework, greater presence at home and reduced presence at the workplace, whereas previous studies have considered only one side of this phenomenon (Alipour et al., 2022; Althoff et al., 2021). By ignoring one side of this phenomenon, previous studies likely underestimate the impact of telework-induced increased presence at home (Alipour et al., 2022) and decreased presence at the workplace (Althoff et al., 2021) on local consumption, since the two components are positively correlated but have opposing effects on transactions. Moreover, explicitly including both demand shocks in the model allows us to capture the net effect of telework on local consumption. Moreover, leveraging high-frequency mobile phone location data and debit/credit card transactions in the Lyon Functional Urban Area (FUA) in September 2022, we provide the first empirical assessment of the day-to-day impact of telework on local consumption.

Our analysis advances the understanding of telework's economic impact by challenging and extending key findings from prior studies. First, we find that telework simultaneously stimulates and suppresses local economic activity, with a one-percentage-point increase in presence of teleworkers at home raises local card spending by 1%, while the same increase in absences from workplace reduces spending by 1.3% (1.7% in terms of transaction count). Second, we provide the first empirical evidence of incomplete substitution between home- and workplace-based consumption: the home-based gains associated with a marginal increase in presence at home offset only about 57–72% of the workplace losses generated by a marginal decrease in presence at work. This discrepancy suggests that telework reduces aggregate spending rather than merely reshuffling it, a critical distinction for assessing its macroeconomic consequences. Third, our study reveals a spatial redistribution of consumption from urban cores to commuting zones, with 81% of municipalities experiencing declines in transaction counts. The 6.8% drop in transactions and 3% decline in spending in Lyon city underscore the vulnerability of high-density employment hubs. Fourth, we demonstrate that these effects are concentrated in central urban areas, where transaction values decline by 3.3% compared to just 0.8% in rural commuting zones, highlighting how telework reduces spatial inequalities. Fifth, our sectoral analysis uncovers heterogeneous impacts: restaurants face sharp declines (24% in urban cores), whereas bars and food retail benefit from residential demand.[19] This heterogeneity suggests that targeted policies could mitigate telework's adverse effects while leveraging its benefits.

Future research could extend this analysis along several dimensions. First, a multi-city comparison using a difference-in-differences framework in the French context could strengthen external validity and test whether our findings generalize beyond Lyon. Such an approach should also integrate both dimensions of telework (the increased presence at home and the reduced presence at the workplace) to provide a more comprehensive assessment of its spatial effects than previously done in the literature. Second, our analysis captures short-term, daily adjustments but does not account for longer-run adaptations by consumers and firms—such as business location changes, entry and exit dynamics, adjustments in local retail supply and employment, or shifts in savings, investment, and broader consumption behavior. Finally, although we document a decline in total in-store spending, the extent to which telework reduces aggregate consumption overall remains uncertain. Our identification strategy builds on the observation that individuals tend to consume more when physically present at the office than when working from home. However, several countervailing mechanisms could influence the overall impact. For instance, savings from reduced commuting and at-home meals may increase disposable income, potentially leading to higher spending during office days or on discretionary purchases (e.g., electronics, home improvements) that our data on in-store transactions does not capture. Additionally, the rise of online

[19]While not directly focused on telework, our results are consistent with studies on COVID-19 mobility restrictions, which offer insights into how increased time spent at home affects consumption. For instance, Bounie et al. (2023) document strong declines in in-store spending during the pandemic in France, and Baker et al. (2020) report sharp reductions in U.S. retail and restaurant expenditures.

shopping and delivery services, accelerated by telework, may further complicate the net effect on total consumption. Investigating these channels would provide a more complete picture of how telework reshapes not just the location and timing of spending, but also its overall volume and composition, with significant implications for the economic geography of post-pandemic cities.

References

Alipour, J.-V., O. Falck, S. Krause, C. Krolage, and S. Wichert (2022). Working from Home and Consumption in Cities. SSRN Electronic Journal.

Althoff, L., F. Eckert, S. Ganapati, and C. Walsh (2021, August). The Geography of Remote Work. Technical Report w29181, National Bureau of Economic Research, Cambridge, MA.

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

Baker, S. R., R. Farrokhnia, S. Meyer, M. Pagel, and C. Yannelis (2020). How does houshold spendind respond to an epidemic? Consumption during the 2020 COVID-19 pandemic. NBER WORKING PAPER SERIES (26949).

Barrero, J. M., N. Bloom, and S. J. Davis (2021). Why Working from Home Will Stick. NBER WORKING PAPER SERIES (28731).

Beck, S., M.-P. De Bellefon, J. Forest, M. Gerardin, and D. Levy (2022). La grille communale de densité à 7 niveaux. Documents de travail Insee (18).

Behrens, K., S. Kichko, and J.-F. Thisse (2024, March). Working from home: Too much of a good thing? Regional Science and Urban Economics 105, 103990.

Belsley, D. A., E. Kuh, and R. E. Welsch (2005, February). Regression Diagnostics: Identifying Influential Data and Sources of Collinearity. John Wiley & Sons. Google-Books-ID: GECBEUJVNe0C.

Bergeaud, A., J.-B. Eyméoud, T. Garcia, and D. Henricot (2021, November). Working From Home and Corporate Real Estate. Place: Rochester, NY Type: SSRN Scholarly Paper.

Borusyak, K., P. Hull, and X. Jaravel (2025, February). A Practical Guide to Shift-Share Instruments. Journal of Economic Perspectives 39(1), 181–204.

Bounie, D., Y. Camara, and J. W. Galbraith (2023, January). Consumer mobility and expenditure during the COVID-19 containments: Evidence from French transaction data. European Economic Review 151, 104326.

Buckman, S. R., J. M. Barrero, N. Bloom, and S. J. Davis (2025). Measuring work from home. NBER WORKING PAPER SERIES.

Dalton, M., M. Dey, and M. Loewenstein (2023). The impact of remote work on local employment, business relocation, and local home costs. BLS WORKING PAPERS 253.

De Fraja, G., J. Matheson, P. Mizen, J. Rockey, and S. Taneja (2026). Remote working and the new geography of local service spending. Economica 93(369), 188–208. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/ecca.70014.

Delventhal, M. J., E. Kwon, and A. Parkhomenko (2022, January). JUE Insight: How do cities change when we work from home? Journal of Urban Economics 127.

Denagiscarde, O. (2025). Working From Home and the Centrality Premium: Implications for Business Districts.

Dingel, J. I. and B. Neiman (2020). How Many Jobs Can be Done at Home? NBER WORKING PAPER SERIES (26948).

Gokan, T., S. Kichko, J. Matheson, and J.-F. Thisse (2022). How the Rise of Teleworking Will Reshape Labor Markets and Cities. SSRN Electronic Journal.

Goux, D. and E. Maurin (2025, November). Sick of Working from Home? The Economic Journal 135(672), 2549–2566.

Hallépée, S. and A. Mauroux (2019, November). Quels sont les salariés concernés par le télétravail ? Dares Analyses 051.

Horowitz, J. L. (2001, January). Chapter 52 - The Bootstrap. In J. J. Heckman and E. Leamer (Eds.), Handbook of Econometrics, Volume 5, pp. 3159–3228. Elsevier.

Hostettler Macias, L., E. Ravalet, and P. Rérat (2022, September). Potential rebound effects of teleworking on residential and daily mobility. Geography Compass 16(9), e12657.

Kiko, M., N. Coulombel, A. Poulhès, T. Seregina, and G. Tremblin (2024, March). Evaluation of Direct and Indirect Effects of Teleworking on Mobility: The Case of Paris. Transportation Research Record: Journal of the Transportation Research Board 2678(3), 865–878.

Kyriakopoulou, E. and P. M. Picard (2023, December). The Zoom city: working from home, urban productivity and land use. Journal of Economic Geography 23(6), 1397–1437.

Li, W. and Y. Su (2026, February). The great reshuffle: Remote work and residential sorting. European Economic Review 182, 105195.

Miyauchi, Y., K. Nakajima, and S. J. Redding (2025, October). The Economics of Spatial Mobility: Theory and Evidence Using Smartphone Data. The Quarterly Journal of Economics 140(4), 2507–2570.

Pierce, D. A. (1982). The Asymptotic Effect of Substituting Estimators for Parameters in Certain Types of Statistics. The Annals of Statistics 10(2), 475–478. Publisher: Institute of Mathematical Statistics.

Ramani, A. S. and N. Bloom (2021). The Donut Effect of Covid-19 on Cities. National Bureau of Economic Research (w28876).

Silva, J. M. C. S. and S. Tenreyro (2006). The Log of Gravity. The Review of Economics and Statistics 88(4), 641–658. Publisher: The MIT Press.

Territoires, G. P. (2022, February). Exode urbain. Un mythe, des réalités. Technical report, Groupement d'intérêt public interministériel européen des projets architecturaux et urbains, Programme POPSU Territoires.

Wooldridge, J. M. (2015, March). Control Function Methods in Applied Econometrics. Journal of Human Resources 50(2), 420–445. Publisher: University of Wisconsin Press Section: Symposium on Empirical Methods.

A Appendix to Section 2

A.1 Lyon FUA and municipalities classification

Figure 4 illustrates the geographic context of the study by displaying a map of France with the Lyon Functional Urban Area (FUA) highlighted. Figure 5 presents a detailed classification of municipalities within the Lyon FUA categorized into four distinct groups: Lyon city (the central urban core), the rest of the urban core (surrounding municipalities within the core area), urban municipalities in the commuting zone (peri-urban areas with higher population density), and rural municipalities in the commuting zone (less densely populated areas on the outskirts). This classification highlights the spatial heterogeneity within the Lyon FUA, which is essential for analyzing how telework impacts different types of municipalities.

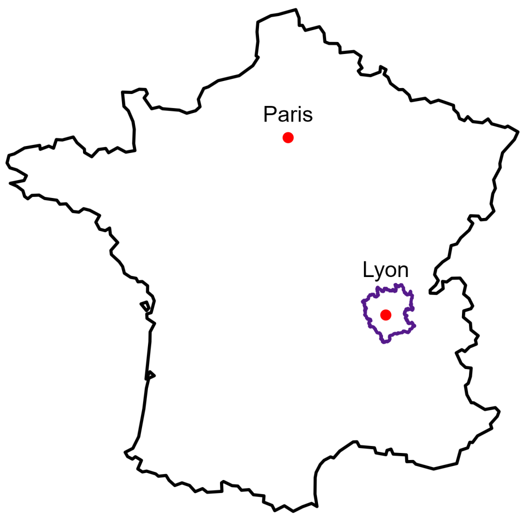


Figure 4: Lyon Functional Urban Area (FUA) in France

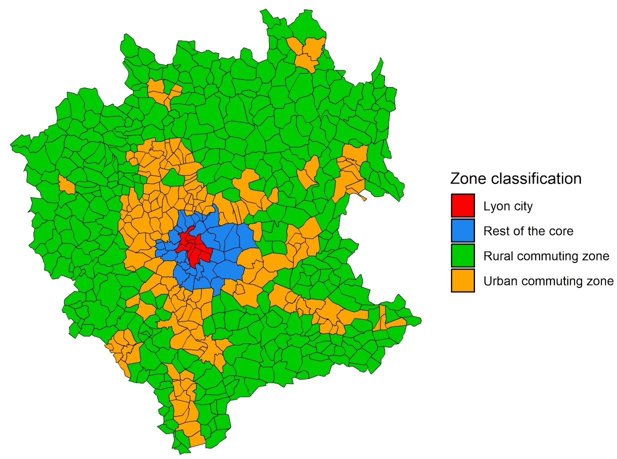


Figure 5: Classification of municipalities in the Lyon FUA

A.2 Mobile Phone Data: Presence of Residents

This part examines the variation in the count of people present in their residential area during weekdays over working hours. We exploit mobile phone data to capture the daily presence patterns of residents, which provides a fine-grained proxy for how teleworking and commuting practices affect local population density.

We estimate the following linear model for the residents' presence share:

$$\text{Residents share}_{idt} = \alpha + \sum_{D} \beta_D \, \mathbb{1}(d \in D) + \varepsilon_{idt}, \tag{8}$$

where i indexes the geographic unit at the Iris level, d represents the specific date of observation, and t denotes 30-minute time slots during the morning working hours from 09:00 to 12:00. The variable Residents share$_{idt}$ measures the ratio of resident volumes during each time slot to the average resident volume observed during the reference period of 06:00–06:30 on the same day, thereby standardizing for daily baseline presence levels. Our analysis focuses on weekdays $D \in \{\text{Tuesday, Wednesday, Thursday, Friday}\}$, using Monday as the reference day. The parameter α captures the average share of residents present during working hours on Monday, establishing our baseline level of residential presence. For each subsequent weekday D, the coefficients β_D quantify the deviation in residential presence relative to this Monday baseline, allowing us to identify systematic intra-week variations in residential presence patterns while controlling for time-of-day effects through our normalization procedure.

To account for heterogeneity across Iris and interaction with teleworking practices, we extend the model as:

$$\begin{aligned} \text{Residents share}_{idt} = \alpha_i &+ \sum_{D} \beta_D \, \mathbb{1}(d \in D) \\ &+ \sum_{D} \gamma_D \, \mathbb{1}(d \in D) \times \text{TE}_i^{(\mathcal{H})} \\ &+ \varepsilon_{idt}, \end{aligned} \tag{9}$$

where $\text{TE}_i^{(\mathcal{H})}$ represents the share of residents who telework at least once per week in Iris i.

Table 8 presents the baseline daily patterns of residents' presence. Column (1) reports the simple day-of-week deviations, while Column (2) includes Iris fixed effects, capturing local heterogeneity. The results show systematic differences across weekdays, with lower presence on Tuesday and Thursday relative to Monday and slightly higher presence on Wednesday and Friday.

	Residents share	
	(1)	(2)
Constant	64.2***	
	(0.271)	
Tuesday	-2.74***	-2.88***
	(0.051)	(0.056)
Wednesday	0.917***	1.10***
	(0.045)	(0.061)
Thursday	-3.21***	-3.35***
	(0.050)	(0.072)
Friday	1.42***	1.66***
	(0.045)	(0.082)
Fixed-effects		
Iris		✓
Fit statistics		
Observations	122,685	122,685
R^2	0.02118	0.66553
Within R^2		0.06866

Note: Signif. codes: ***: 0.01, **: 0.05, *: 0.1. Clustered standard-errors at the iris level in parentheses.

Table 8: Daily patterns of presence in the residence zone

Table 9 introduces interactions with teleworking shares ($TE^{(\mathcal{H})}$). Positive and significant coefficients indicate that areas with higher shares of teleworkers experience larger fluctuations in resident presence across the week. We also account for interactions with the share of part-time workers among residents ($PT^{(\mathcal{H})}$), which show smaller yet occasionally significant effects. Importantly, including these controls does not alter the magnitude or significance of the coefficients associated with residents' telework shares, neither the goodness of fit, suggesting that weekly variations in home presence are primarily driven by teleworkers' mobility patterns.

	Residents share	
	(1)	(2)
Tuesday	-3.4***	-4.1***
	(0.17)	(0.40)
Wednesday	0.18	-0.81**
	(0.17)	(0.18)
Thursday	-3.9***	-4.6***
	(0.23)	(0.53)
Friday	-1.8***	-2.7***
	(0.23)	(0.36)
Tuesday × $TE^{(\mathcal{H})}$	0.03**	0.03**
	(0.009)	(0.009)
Wednesday × $TE^{(\mathcal{H})}$	0.05***	0.06***
	(0.008)	(0.010)
Thursday × $TE^{(\mathcal{H})}$	0.04**	0.04**
	(0.01)	(0.01)
Friday × $TE^{(\mathcal{H})}$	0.20***	0.20***
	(0.01)	(0.01)
Tuesday × $PT^{(\mathcal{H})}$		0.04
		(0.03)
Wednesday × $PT^{(\mathcal{H})}$		0.05**
		(0.01)
Thursday × $PT^{(\mathcal{H})}$		0.03
		(0.03)
Friday × $PT^{(\mathcal{H})}$		0.05***
		(0.010)
Iris fixed effects	✓	✓
Observations	119,690	119,690
R^2	0.66806	0.66812
Within R^2	0.07208	0.07224

Note: Signif. codes: ***: 0.01, **: 0.05, *: 0.1. Clustered standard-errors at the iris level in parentheses.

Table 9: Daily variation in resident presence by $TE^{(\mathcal{H})}$ levels

To make these results more interpretable, Table 10 reports the predicted deviations in resident presence for Iris with different teleworker shares (10%, 20%, and 30%). For example, in areas with 30% teleworkers, the share of residents present increases by over 4 percentage points on Friday relative to Monday, highlighting the substantial influence of teleworking on daily presence patterns.

Overall, these results demonstrate that the greater the share of teleworkers in a residential area, the larger the weekday variation in local presence, reflecting the structural impact of hybrid work on urban activity patterns.

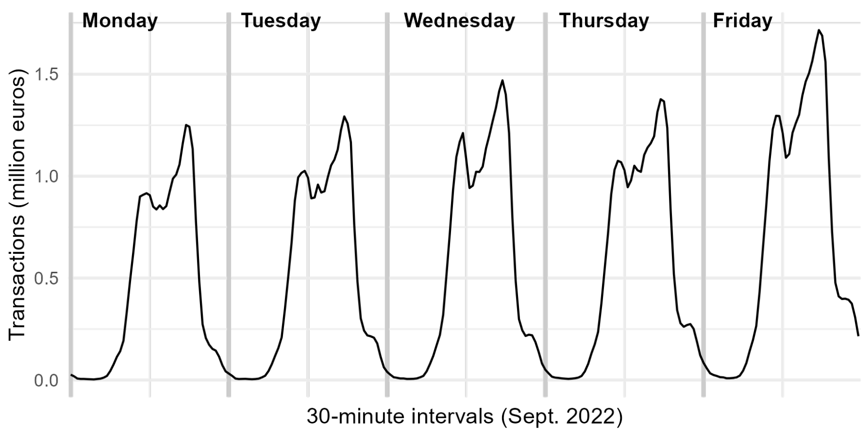
Day	**TE$^{(\mathcal{H})}$ = 10%**	**TE$^{(\mathcal{H})}$ = 20%**	**TE$^{(\mathcal{H})}$ = 30%**
Monday	ref	ref	ref
Tuesday	-3.07	-2.79	-2.51
Wednesday	0.71	1.24	1.78
Thursday	-3.58	-3.22	-2.85
Friday	0.21	2.18	4.15

Note: The table shows the expected daily variation in resident presence relative to Monday, by levels of TE$^{(\mathcal{H})}$, as predicted from the estimates in Table 9.

Table 10: Daily variation in resident presence by TE$^{(\mathcal{H})}$ levels

A.3 Card daily total spending in Lyon FUA

Figure 6 presents the daily total card spending in the Lyon Functional Urban Area (FUA) across a typical weekday in September 2022. This figure provides a snapshot of how spending varies by day of the week, highlighting patterns in consumer behavior and economic activity within the metropolitan area. It shows that consumer spending in the Lyon FUA is not uniform across weekdays, with notable peaks on Wednesdays and Fridays.



Note: The figure shows total daily card spending from our sample of observed transactions within the Lyon Functional Urban Area (FUA) across weekdays in September 2022.

Figure 6: Typical weekday card spending

B Appendix to Section 3

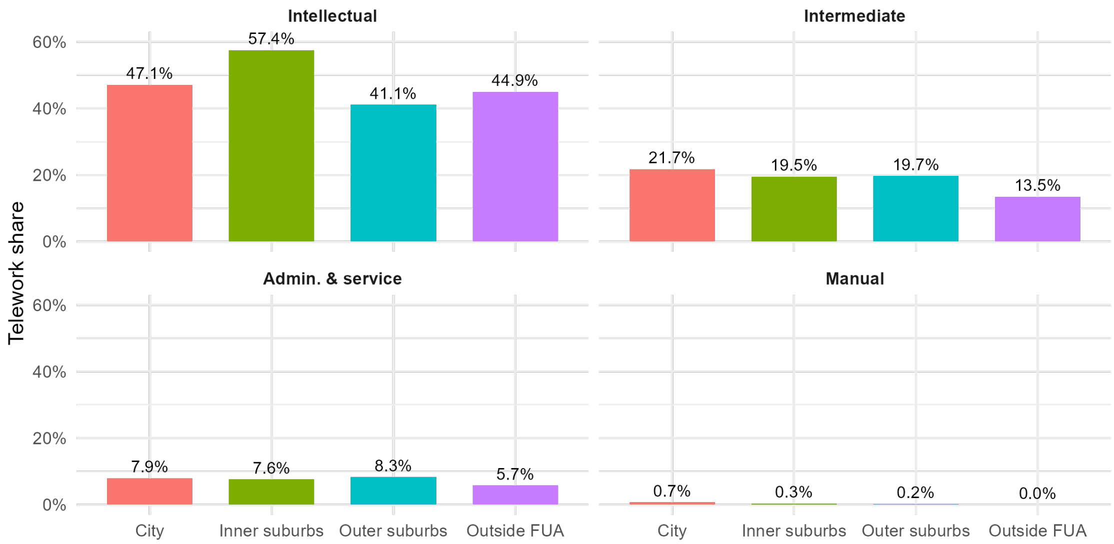
B.1 Telework statistics

Table 11 shows the evolution of the overall share of teleworkers among workers from 2017-2024, and by occupation. It shows that after covid-19 pandemic, telework practice sticked. Figure 7 shows the different teleworkers shares among workers by occupation and residence municipality group within the FUA.

	2017	2021	2022	2023	2024
Teleworkers share (in %)					
Executives and Higher Intellectual Professions	11.1	55.4	51.7	49.5	47.9
Intermediate Professions	3.2	22.1	19.0	16.7	17.7
Administrative and Service Workers	1.4	9.7	8.8	7.7	7.5
Manual Workers	0.2	0.3	0.2	0.3	0.2
All	**3.0**	**21.7**	**19.2**	**18.4**	**18.3**
Average Telework Days per Week, Conditional on Teleworking					
Executives and Higher Intellectual Professions	-	3.4	2.7	2.5	2.5
Intermediate Professions	-	3.0	2.6	2.3	2.2
Administrative and Service Workers	-	3.1	2.7	2.3	2.4
Manual Workers	-	3.0	1.9	2.3	2.7
All	**1.9**	**3.3**	**2.7**	**2.4**	**2.4**

Note: The table displays the proportion of teleworkers among employed workers aged 15 and older, categorized by aggregated professional groups, from 2017 to 2024. Additionally, it provides the average number of telework days over a typical week, conditional on engaging in telework. Statistics for 2017 are from Hallépée and Mauroux (2019), Table 1, which exploit data from *Dares-DGT-DGAFP* and *Enquête Sumer 2017*. The other statistics were derived from our calculations, using the *Enquête Emploi en Continu*, from 2021 to 2024.

Table 11: Telework practice by aggregated professional category in France from 2017 to 2024

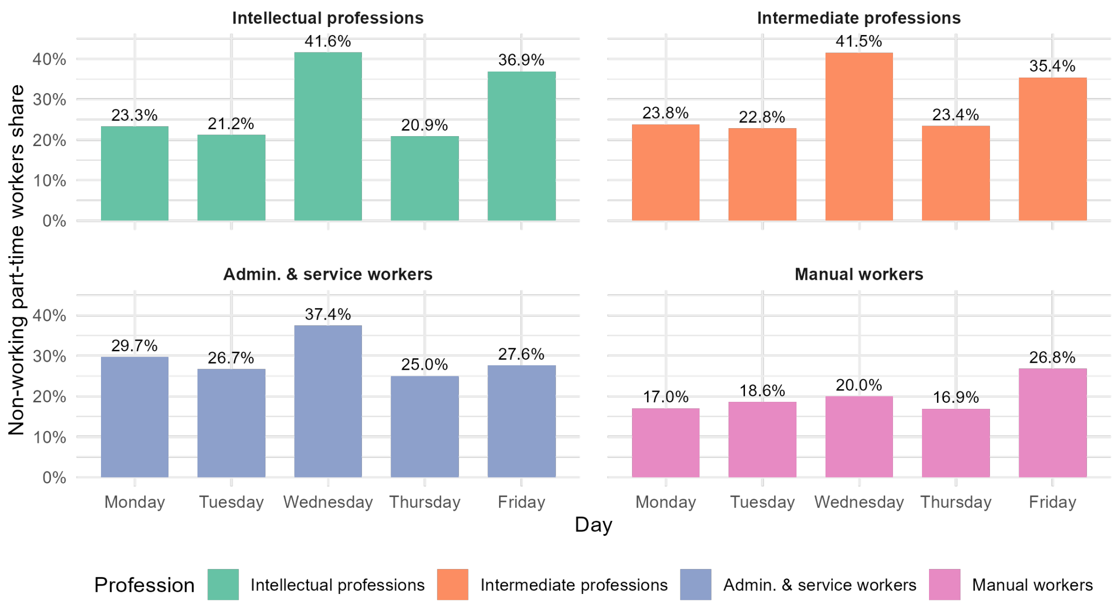


Note: The table reports the proportion of teleworkers among employed individuals aged 15 and over, by occupation and place of residence within Functional Urban Areas (FUAs) in the Auvergne–Rhône-Alpes region, where Lyon is located. Estimates are computed from the *Enquête Emploi en Continu*, fourth quarter of 2022.

Figure 7: Telework shares by occupation and residence location within FUA

B.2 Non-working part-time workers on day-off

To isolate the causal effect of telework on local consumption, it is essential to account for the presence of part-time workers who are not working on specific weekdays. These individuals may stay at home or engage in local activities on their days off, potentially confounding the estimated impact of telework on consumption patterns. Their presence could be mistakenly attributed to telework-induced home presence, leading to biased estimates of the telework effect. Figure 8 illustrates the daily variation in the share of part-time workers who are on their day off, broken down by occupation group and weekday (Monday to Friday).



Note: The table reports the proportion of part-time workers on their day off among all part-time workers (employed individuals aged 15 and over), by occupation and day of the week. Estimates are computed from the *Enquête Emploi en Continu*, fourth quarter of 2022, for Functional Urban Areas (FUAs) in the Auvergne–Rhône-Alpes region.

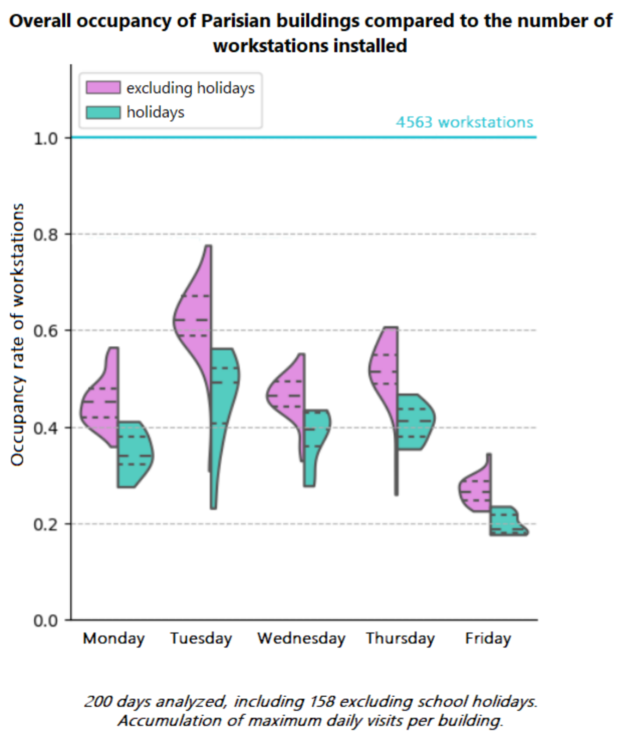
Figure 8: Share of part-time workers on day-off per weekday and occupation

B.3 External Validation: On-site Presence Data from a Paris-based Public Institution

A large Paris-based public institution conducted an exploratory analysis using on-site presence data collected via access control systems across its nine office buildings between October 2022 and February 2024. These buildings are occupied almost exclusively by executives and higher intellectual professions, which constitute the most teleworkable category of workers.

The institution has kindly authorized us to present their findings, which serve as an external validation of our model-based estimates of daily working from home shares among teleworkers. As shown in Figure 9, the observed weekday on-site presence rates (excluding holiday periods) closely align with our estimated shares of employees working from home reported in Table 1, thereby reinforcing the empirical credibility of our results.

In particular, the analysis reveals pronounced weekly patterns in on-site presence. Tuesday is the peak attendance day, with an average presence rate of 62%. Thursday follows with a slightly lower but still high rate of 52%. Monday and Wednesday show intermediate attendance levels of around 45%, while Friday stands out with markedly low on-site presence at 25%. Some heterogeneity in attendance levels was also observed across buildings within each day of the week.



Note: The figure shows the distribution of building occupancy rates across weekdays for an anonymized public institution in Paris. Each violin represents the density of occupancy observations for a given day, with the central dashed line indicating the median and the two other dashed bars marking the 25th and 75th percentiles.

Figure 9: On-site presence rates by weekday

These presence rates would translate into telework shares of 55% on Monday (compared with

52% in our findings), 38% on Tuesday (26%), 55% on Wednesday (62%), 48% on Thursday (24%), and 75% on Friday (78%). Overall, this corresponds to an average of 2.7 teleworked days per week, compared with 2.4 in our analysis. The slightly higher telework intensity observed in this institution can be explained by its specific context: all employees are eligible for telework, there are no formal restrictions on telework days, and the buildings are located in central Paris, where commuting constraints are more significant.

For more details about the methodology: The dataset comprised approximately 260,000 hourly presence records covering the period from October 2022 to February 2024, with earlier data available from mid-2022 for some sites. To ensure comparability across days, lunchtime counts (11:30–14:30) were excluded to avoid biases from off-site movements. Data cleaning also led to the removal of about 22,000 anomalous observations, including days with incomplete measurements, extreme or abnormal night-time values, and days identified as building closures (defined as less than 10% of usual attendance). Ultimately, 200 valid working days were retained for the nine buildings over the 356 working days in the reference period.

C Appendix to Section 4

C.1 Business sectors and aggregate groups

Section C.1 provides a detailed classification of retail and service activities used in the study to analyze the sectoral impacts of telework on local consumption. Table 12 maps NAF codes (Nomenclature d'Activités Française) to aggregated sector categories, which are used to examine how telework affects different types of businesses in the Lyon Functional Urban Area (FUA).

Food Retail	**General Retail**	**Clothing and Beauty Retail**	**Health and Wellness Retail**
4711A: Retail sale of frozen products	4726Z: Retail sale of tobacco products	4771Z: Retail sale of clothing	4773Z: Retail sale of pharmaceutical products
4711B: Retail sale in general stores	4741Z: Retail sale of computers	4772A: Retail sale of footwear	4774Z: Retail sale of medical and orthopedic goods
4711C: Convenience stores	4742Z: Retail sale of telecommunications equipment	4772B: Retail sale of leather goods	4778A: Retail sale of optical goods
4711D: Supermarkets	4743Z: Retail sale of audio and video equipment	4775Z: Retail sale of perfumes and cosmetics	
4711E: Mixed retail stores	4751Z: Retail sale of textiles	4777Z: Retail sale of watches and jewelry	
4711F: Hypermarkets	4752A: Retail sale of hardware (small stores)		
4719A: Department stores	4752B: Retail sale of hardware (large stores)		
4719B: Other non-specialized retail	4753Z: Retail sale of carpets and floor coverings		
4721Z: Retail sale of fruit and vegetables	4754Z: Retail sale of household appliances		
4722Z: Retail sale of meat and meat products	4759A: Retail sale of furniture		
4723Z: Retail sale of fish and seafood	4759B: Retail sale of other household equipment		
4724Z: Retail sale of bread and pastries	4761Z: Retail sale of books		
4725Z: Retail sale of beverages	4762Z: Retail sale of newspapers and stationery		
4729Z: Other food retail	4763Z: Retail sale of music and video recordings		
	4764Z: Retail sale of sporting goods		
	4765Z: Retail sale of games and toys		
	4776Z: Retail sale of flowers, plants, and pet supplies		
	4778B: Retail sale of coal and fuels		
	4778C: Other specialized retail trade		
	4779Z: Retail sale of second-hand goods		
Restaurants	**Bars and Drinks**	**Arts and Entertainment**	**Museums and Cultural Sites**
5610A: Traditional restaurants	5630Z: Beverage serving activities	9001Z: Performing arts	9102Z: Operation of museums
5610B: Cafeterias and self-service restaurants		9002Z: Support activities for performing arts	9103Z: Operation of historical sites
5610C: Fast food restaurants		9003A: Artistic creation in visual arts	9104Z: Operation of botanical and zoological gardens
5621Z: Catering services		9003B: Other artistic creation	
5629A: Contract catering		9004Z: Operation of arts facilities	
5629B: Other food service activities			
Gambling	**Sports and Recreation**	**Accommodations**	**Automotive**
9200Z: Gambling and betting activities	9311Z: Operation of sports facilities	5510Z: Hotels and similar accommodation	4511Z: Sale of cars and light motor vehicles
	9312Z: Activities of sports clubs	5520Z: Holiday and short-stay accommodation	4519Z: Sale of other motor vehicles
	9313Z: Fitness and physical well-being activities	5530Z: Camping grounds and recreational vehicle parks	4520A: Maintenance and repair of light motor vehicles
	9319Z: Other sports activities	5590Z: Other accommodation	4532Z: Retail sale of motor vehicle parts and accessories
	9321Z: Amusement and theme park activities		4540Z: Sale and repair of motorcycles
	9329Z: Other amusement and recreation activities		4730Z: Retail sale of automotive fuel

Note: The table maps NAF codes (*Nomenclature d'Activités Française*) of physical stores, businesses, restaurants, and cafés included in our sample of card transactions within the Lyon Functional Urban Area to aggregated sector categories.

Table 12: Classification of Retail and Service Activities

C.2 Robustness Checks and Sensitivity Analyses

To ensure the robustness and validity of our empirical findings, this appendix presents a comprehensive set of analyses organized into three complementary part. First, we conduct rigorous robustness checks to assess the stability of our results against potential biases, including examinations of multicollinearity, omitted variable bias, and alternative model specifications. Second, we perform extensive sensitivity analyses to evaluate how our results respond to alternative assumptions and data specifications. This includes assessments of measurement errors, alternative definitions of telework, and variations in model specifications. Finally, we implement advanced causal identification strategies to strengthen the causal interpretation of our results. These include instrumental variable approaches and alternative identification methods designed to address potential endogeneity and measurement error, thereby enhancing the credibility of our causal inferences.

C.2.1 Robustness Checks

First, we conduct rigorous robustness checks to verify that our core results remain stable across different modeling specifications and are not sensitive to potential biases.

Multicollinearity. To evaluate potential multicollinearity in our estimation framework, we employ a rigorous diagnostic approach centered on the condition number of the Hessian matrix. This metric, defined as the ratio between the largest and smallest singular values, serves as a robust indicator of multicollinearity when exceeding the threshold of 30 as established by Belsley et al. (2005). Our empirical diagnostics reveal condition numbers substantially below this critical threshold, registering values of 4 in our baseline specification (Table 2) and approximately 15 in our fully specified models incorporating the complete set of control variables. These consistently low condition numbers across all model specifications provide compelling evidence against significant multicollinearity concerns. Furthermore, the remarkable stability of our coefficient estimates across different model configurations reinforces this conclusion, demonstrating that our identification strategy remains robust against potential linear dependencies among regressors.

While our multicollinearity diagnostics yield reassuring results, we further investigate a more subtle identification challenge stemming from potential double-counting in our telework measures. Specifically, workers who both reside and work within the same municipality could be inadvertently counted in both our residential and workplace telework indicators, potentially introducing bias in our estimates. To address this concern, we construct an alternative telework measure that focuses exclusively on telecommuters, workers who commute to offices located outside their municipality of residence on specific days. This refined measure explicitly excludes the 12.9% of potential teleworkers (median: 11.5%) who both live and work in the same municipality, thereby eliminating any risk of double-counting. The results of this robustness check, presented in Table 13, demonstrate exceptional stability in our coefficient estimates when using this alternative specification. This consistency across different operationalizations of our telework variables provides definitive evidence that our core findings are not artifacts of potential double-counting bias, thereby further strengthening the credibility of our identification strategy.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Transaction count							
$\text{RT}^{(\mathcal{H})}_{\text{telecommuters}}$	1.07***	1.01***	1.08***	1.08***	1.07***	1.02***	1.01***
	(0.260)	(0.287)	(0.258)	(0.259)	(0.261)	(0.268)	(0.286)
$\text{RT}^{(\mathcal{W})}_{\text{telecommuters}}$	-1.08***	-0.936***	-1.07***	-1.07***	-1.08***	-1.03***	-0.931***
	(0.274)	(0.275)	(0.274)	(0.274)	(0.275)	(0.273)	(0.276)
$\text{PT}^{(\mathcal{H})}$		0.340					0.358
		(1.01)					(1.01)
$\text{PT}^{(\mathcal{W})}$		2.72***					2.74***
		(0.769)					(0.768)
Rain			-0.007				-0.008
			(0.005)				(0.005)
Light rain				-0.007			
				(0.005)			
Moderate rain				-0.013			
				(0.012)			
Public transp. disrupt.					0.006	-0.0004	0.006
					(0.009)	(0.019)	(0.009)
$\text{RT}^{(\mathcal{H})}_{\text{telecommuters}}$ × Public transp. disrupt.						0.561	
						(0.369)	
$\text{RT}^{(\mathcal{W})}_{\text{telecommuters}}$ × Public transp. disrupt.						-0.464	
						(0.366)	
Fit statistics							
Observations	10,640	10,640	10,640	10,640	10,640	10,640	10,640
BIC	5,418,671.1	5,397,893.5	5,417,550.8	5,417,339.2	5,417,764.9	5,413,410.1	5,395,551.3
Inferred work-to-home consumption substitution rate							
$\lvert\frac{\theta_1}{\theta_2}\rvert$	0.802***	0.657***	0.81***	0.808***	0.802***	0.747***	0.664***
	(0.241)	(0.215)	(0.243)	(0.243)	(0.237)	(0.229)	(0.214)
Panel B: Transaction value							
$\text{RT}^{(\mathcal{H})}_{\text{telecommuters}}$	0.886***	0.705***	0.891***	0.891***	0.885***	0.791***	0.707***
	(0.181)	(0.175)	(0.178)	(0.178)	(0.180)	(0.181)	(0.173)
$\text{RT}^{(\mathcal{W})}_{\text{telecommuters}}$	-1.11***	-1.07***	-1.10***	-1.10***	-1.10***	-1.06***	-1.07***
	(0.308)	(0.298)	(0.307)	(0.307)	(0.302)	(0.278)	(0.290)
$\text{PT}^{(\mathcal{H})}$		1.48					1.50
		(1.04)					(1.03)
$\text{PT}^{(\mathcal{W})}$		1.13					1.15
		(0.741)					(0.739)
Rain			-0.009*				-0.010**
			(0.005)				(0.005)
Light rain				-0.009**			
				(0.005)			
Moderate rain				-0.015			
				(0.011)			
Public transp. disrupt.					0.009	-0.012	0.009
					(0.007)	(0.017)	(0.007)
$\text{RT}^{(\mathcal{H})}_{\text{telecommuters}}$ × Public transp. disrupt.						0.809*	
						(0.449)	
$\text{RT}^{(\mathcal{W})}_{\text{telecommuters}}$ × Public transp. disrupt.						-0.561	
						(0.427)	
Fit statistics							
Observations	10,640	10,640	10,640	10,640	10,640	10,640	10,640
BIC	166,780.4	166,540.4	166,732.0	166,737.6	166,732.4	166,463.2	166,437.7
Inferred work-to-home consumption substitution rate							
$\lvert\frac{\theta_1}{\theta_2}\rvert$	0.998***	1.082***	1.007***	1.005***	0.997***	0.988***	1.09***
	(0.298)	(0.378)	(0.303)	(0.302)	(0.297)	(0.314)	(0.386)

Note: Signif. codes: ***: 0.01, **: 0.05, *: 0.1. Clustered standard-errors at the municipality level in parentheses. All specifications include municipality and date-by-zone type fixed effects. Standard errors of the inferred work-to-home consumption substitution rate, $\lvert\frac{\theta_1}{\theta_2}\rvert$, are computed using the Delta Method.

Table 13: Transaction count and value responses to telecommute shares

Omitted Variable Bias. A potential source of bias arises from the correlation between telework shares and the regression error term, which may distort the estimates of θ_1 and θ_2. To mitigate this, we control for the daily share of part-time workers who are on a day off, as their preferred days off often coincide with the days teleworkers choose to work from home. We distinguish between their place of residence (where they are likely to be present when not working), $\mathrm{PT}_{it}^{(\mathcal{H})}$, and their place of work (where they are expected to be absent), $\mathrm{PT}_{it}^{(\mathcal{W})}$. We additionally control for two types of events that may limit mobility, including the decision to work from home, and modify consumption behaviors: (1) rainy days and rain intensity; and (2) disruptions in the local public transport network (TCL) during morning commuting hours.

Interesting results arise (Table 2): part-time workers on their day off contribute significantly to local consumption. For example, the share of part-time workers at home increases from 3.43% on Tuesday to 5.89% on Wednesday, a change associated with a 4.2% rise in transactions. This effect remains below the 5.7% increase linked to the rise in home-based telework (from 3.95% to 9.61% over the same period), even though part-time workers have more free time for local spending than teleworkers working from home. This gap could reflect income differences: part-time workers tend to earn less than the average teleworker, who is often an executive. Additionally, this control affects the estimated telework coefficients by reducing their magnitude. This is expected, since teleworkers and part-time workers tend to favor the same days to stay at home.

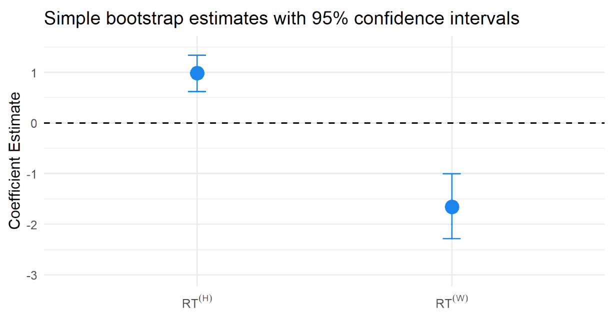
Rain reduces transactions by about 1% on average (significant at the 5% level), with stronger effects under heavier rainfall. Including this control leaves the estimated telework coefficients unchanged, suggesting limited confounding from weather conditions. Public transport disruption do not have a statistically significant direct effect on local consumption levels. However, their interaction with telework shares reveals an interesting pattern: disruptions amplify both the positive effect of telework at place of residence and its negative effect at the workplace. This likely reflects that public transport disruption reduce commuting: when disruptions occur during the morning commute, more teleworkers may choose to stay and work from home. Even if these disruptions do not directly lower consumption, they may shift where spending takes place, reinforcing the spatial reallocation of consumption driven by telework.

Bootstrapped Standard Errors. As a critical component of our robustness checks, we examine the potential for biased standard errors arising from our multi-step estimation procedure. Given that our explanatory variables are generated using parameters estimated in a prior OLS regression step, conventional standard errors may underestimate the true uncertainty in our estimates. This concern is particularly relevant for our identification strategy, where the construction of generated regressors could introduce additional variability not captured by standard inference procedures.

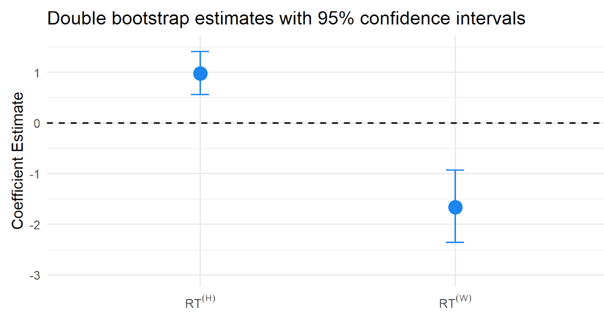
Our bootstrap procedure follows a rigorous multi-stage process designed to account for all potential sources of estimation uncertainty. Initially, we randomly resample clusters of municipalities with replacement to create alternative samples of our data. For each resampled dataset, we then re-estimate the first-step coefficient (β_t) that captures the daily share of teleworkers working from home. Using these newly estimated parameters, we reconstruct the generated telework regressors. Finally, we re-estimate our complete model, repeating this entire process across 1,000 iterations to build a comprehensive distribution of our estimated coefficients.

This methodology follows established best practices for inference with multi-step estimation as outlined by (Horowitz, 2001), ensuring that our standard errors remain robust to within-cluster dependence and properly account for the uncertainty inherent in our generated regressors. By capturing both sampling variation and the additional uncertainty introduced through the construction of generated variables, our approach provides more reliable confidence intervals for all parameter estimates.

The results of our bootstrap analysis are presented in Figures 10 and 11. Figure 10 compares the telework coefficients and their confidence intervals obtained through both simple and double cluster bootstrap methods. As theoretically expected, the double bootstrap procedure yields wider confidence intervals, reflecting its more comprehensive accounting for all sources of uncertainty in our estimation process. Crucially, despite these appropriately wider intervals, our coefficients remain statistically significant in both cases, providing strong evidence for the robustness of our core findings.



(a) Simple

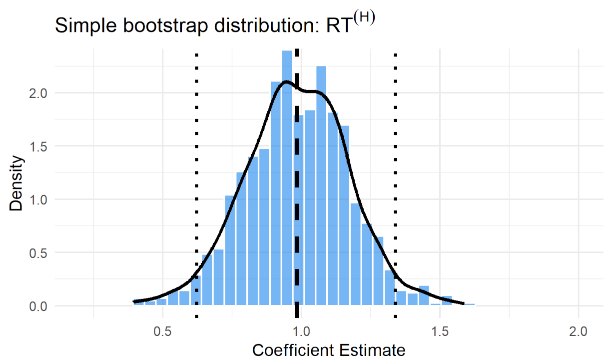


(b) Double

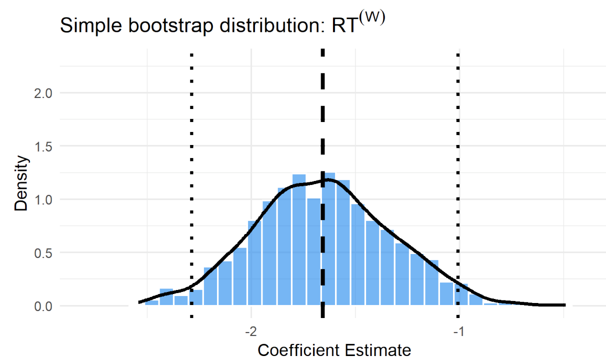
Note: This figure presents the estimates of a one percentage point increase in $\mathrm{RT}^{(\mathcal{H})}$ and $\mathrm{RT}^{(\mathcal{W})}$, using both simple and double bootstrap procedures. Each estimate is shown with 95% confidence intervals, computed using standard-errors clustered at the municipality level. The simple bootstrap applies to model 4, with 1,000 re-samplings with replacement of municipalities. The double bootstrap extends this procedure by also re-estimating model 3 within each iteration to regenerate the telework regressors. Both specifications control for the share of part-time workers present at home and absent from the workplace, rainfall, public transport disruptions, and include municipality and date-by-zone type fixed effects.

Figure 10: Comparison of bootstrapped coefficients and confidence intervals

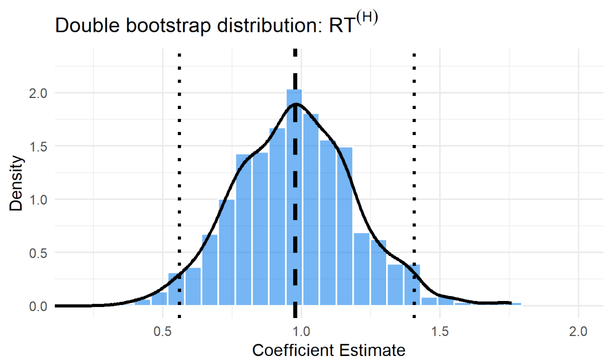
Figure 11 offers additional visual evidence by displaying the complete distribution of estimated coefficients across all bootstrap iterations. The stability of these distributions across different resampling procedures further confirms the reliability of our estimation strategy and the validity of our inference.



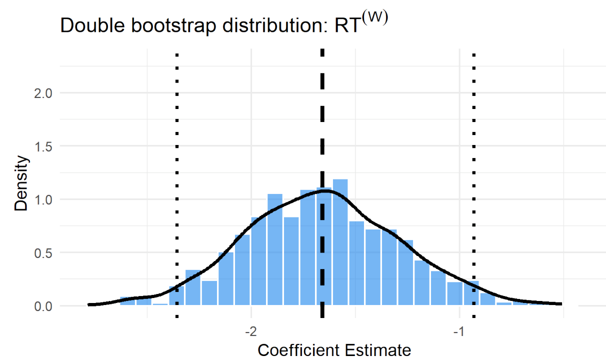
(a) Simple $\text{RT}^{(\mathcal{H})}$



(b) Simple $\text{RT}^{(\mathcal{W})}$



(c) Double $\text{RT}^{(\mathcal{H})}$



(d) Double $\text{RT}^{(\mathcal{W})}$

Note: This figure presents the distribution of the estimates of a one percentage point increase in $\text{RT}^{(\mathcal{H})}$ and $\text{RT}^{(\mathcal{W})}$, using both simple and double bootstrap procedures. Each estimate is shown with its mean value (bold dashed line) and its 95% confidence intervals (fine dashed lines), computed using standard-errors clustered at the municipality level. The simple bootstrap applies to model 4, with 1,000 re-samplings with replacement of municipalities. The double bootstrap extends this procedure by also re-estimating model 3 within each iteration to regenerate the telework regressors. Both specifications control for the share of part-time workers present at home and absent from the workplace, rainfall, public transport disruptions, and include municipality and date-by-zone type fixed effects.

Figure 11: Distribution of bootstrapped coefficients across iterations

Spatial Heterogeneity in Marginal Effects. As a critical component of our robustness checks, we examine whether our estimated semi-elasticity coefficients exhibit systematic variation across different zone groups, which could potentially undermine the generalization of our findings. This analysis is particularly important given the substantial heterogeneity in commercial density and economic activity patterns across urban cores, commuting zones, and rural areas. By investigating potential spatial heterogeneity in our marginal effects, we verify that our core results are not sensitive to specific geographic configurations or local economic structures.

To assess this spatial robustness, we employ an interaction-based approach that incorporates each zone group as proxy variables interacting with our telework shares. This specification allows us to test for statistically significant differences in the impact of telework on local consumption across different types of municipalities. The results, presented in Table 14, reveal that the semi-elasticity coefficients are not statistically significantly different across zone groups.

This finding provides strong evidence for the spatial robustness of our results, indicating that the relationship between telework and local consumption patterns remains consistent regardless of the specific characteristics of different zones. The stability of our estimates across diverse geographic contexts further reinforces the validity and generalization of our core findings.

	Transaction count (1)	Transaction value (2)
$RT^{(\mathcal{H})}$	1.61***	0.469
	(0.587)	(0.750)
$RT^{(\mathcal{W})}$	-2.77**	-1.95
	(1.18)	(1.27)
$PT^{(\mathcal{H})}$	1.68*	0.898
	(0.958)	(0.976)
$PT^{(\mathcal{W})}$	1.37*	2.76***
	(0.788)	(0.786)
Rain	-0.009**	-0.007
	(0.004)	(0.005)
Public transp. disrupt.	0.008	0.006
	(0.007)	(0.009)
$RT^{(\mathcal{H})} \times$ Rest of the core	-0.565	0.751
	(0.700)	(0.886)
$RT^{(\mathcal{H})} \times$ Urban commuting zone	-1.05	0.132
	(0.713)	(0.858)
$RT^{(\mathcal{H})} \times$ Rural commuting zone	-0.168	1.19
	(0.878)	(0.971)
$RT^{(\mathcal{W})} \times$ Rest of the core	0.822	0.364
	(1.39)	(1.52)
$RT^{(\mathcal{W})} \times$ Urban commuting zone	1.55	0.907
	(1.25)	(1.37)
$RT^{(\mathcal{W})} \times$ Rural commuting zone	1.17	0.457
	(1.41)	(1.50)
Fit statistics		
Observations	10,640	10,640
BIC	166,190.1	5,401,213.3

Note: Signif. codes: ***: 0.01, **: 0.05, *: 0.1. Clustered standard-errors at the municipality level in parentheses. All specifications include municipality and date-by-zone type fixed effects.

Table 14: Test of spatial heterogeneity: Transaction count and value responses to telework shares by zone group

C.2.2 Sensitivity Analyses

In this part, we perform extensive sensitivity analyses to explore how our results respond to alternative assumptions and data specifications. These analyses assess the impact of measurement errors, alternative definitions of telework, and different model specifications. By examining these variations, we evaluate whether our conclusions hold under different conditions and potential data limitations.

Standardized Telework Shares This sensitivity analysis examines the robustness of our findings to an important measurement challenge: the asymmetry in variation patterns between residential and workplace telework shares. Our baseline specification implicitly assumes that residential telework ($RT^{(\mathcal{H})}$ and workplace telework ($RT^{(\mathcal{W})}$) exhibit comparable variability across different days, yet our empirical observations demonstrate a substantial asymmetry: residential telework shares vary by +6.03 percentage points between high- and low-telework days, compared to only +4.67 percentage points for workplace shares.

This discrepancy between our modeling assumption and empirical reality creates a potential sensitivity concern. Our substitution rate estimates could be influenced by this differential variability in our key explanatory variables. To systematically evaluate this potential sensitivity, we implement a standardized measurement approach that accounts for the empirical distribution of our telework variables.

We address this measurement asymmetry by re-estimating our regression model using standardized telework shares. In this specification, the coefficients θ_1 and θ_2 represent the percentage change in consumption associated with a one-standard-deviation increase in residential and workplace telework shares, respectively. This standardization enables more accurate comparisons of effects by controlling for the differing empirical distributions of our telework measures.

The results of this sensitivity test, presented in Table 15, demonstrate remarkable consistency with our baseline findings. The estimated substitution rates of 0.64 (95% CI: 0.351-0.927) for transaction counts and 0.80 (95% CI: 0.372-1.230) for transaction values confirm our core conclusion that most municipalities experience net losses in local spending due to telework. Crucially, this consistency persists even after accounting for the differential variability in our telework measures.

The stability of our results across this alternative specification provides compelling evidence that our findings are not sensitive to the specific choice of our telework variables. This robustness to different measurement approaches significantly strengthens the credibility of our empirical conclusions and confirms that our results are not artifacts of our particular measurement strategy.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Transaction count							
$RT_{sd}^{(\mathcal{H})}$	0.045***	0.038***	0.045***	0.045***	0.044***	0.040***	0.038***
	(0.009)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)
$RT_{sd}^{(\mathcal{W})}$	-0.061***	-0.061***	-0.060***	-0.060***	-0.061***	-0.058***	-0.060***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.014)	(0.013)
$PT^{(\mathcal{H})}$		1.66*					1.66*
		(0.978)					(0.967)
$PT^{(\mathcal{W})}$		1.47**					1.49**
		(0.749)					(0.746)
Rain			-0.008*				-0.009**
			(0.004)				(0.004)
Light rain				-0.008*			
				(0.004)			
Moderate rain				-0.014			
				(0.010)			
Public transp. disrupt.					0.009	0.011	0.008
					(0.007)	(0.010)	(0.007)
$RT_{sd}^{(\mathcal{H})} \times$ Public transp. disrupt.						0.028	
						(0.017)	
Public transp. disrupt. $\times RT_{sd}^{(\mathcal{W})}$						-0.022	
						(0.016)	
Fit statistics							
Observations	10,640	10,640	10,640	10,640	10,640	10,640	10,640
BIC	166,692.0	166,326.0	166,657.1	166,662.6	166,645.0	166,472.2	166,239.7
Inferred work-to-home consumption substitution rate							
$\lvert\frac{\theta_1}{\theta_2}\rvert$	0.734***	0.629***	0.744***	0.743***	0.735***	0.682***	0.639***
	(0.163)	(0.147)	(0.163)	(0.163)	(0.163)	(0.162)	(0.147)
Panel B: Transaction value							
$RT_{sd}^{(\mathcal{H})}$	0.041***	0.037***	0.041***	0.041***	0.041***	0.038***	0.038***
	(0.010)	(0.011)	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)
$RT_{sd}^{(\mathcal{W})}$	-0.048***	-0.048***	-0.047***	-0.047***	-0.048***	-0.045***	-0.047***
	(0.014)	(0.014)	(0.013)	(0.013)	(0.014)	(0.014)	(0.014)
$PT^{(\mathcal{H})}$		0.838					0.849
		(0.968)					(0.964)
$PT^{(\mathcal{W})}$		2.92***					2.93***
		(0.764)					(0.763)
Rain			-0.006				-0.007
			(0.005)				(0.005)
Light rain				-0.006			
				(0.005)			
Moderate rain				-0.012			
				(0.012)			
Public transp. disrupt.					0.006	0.016	0.006
					(0.008)	(0.012)	(0.008)
$RT_{sd}^{(\mathcal{H})} \times$ Public transp. disrupt.						0.027**	
						(0.013)	
Public transp. disrupt. $\times RT_{sd}^{(\mathcal{W})}$						-0.026**	
						(0.013)	
Fit statistics							
Observations	10,640	10,640	10,640	10,640	10,640	10,640	10,640
BIC	5,434,198.5	5,407,037.1	5,433,319.9	5,433,133.1	5,433,321.2	5,428,426.3	5,404,987.2
Inferred work-to-home consumption substitution rate							
$\lvert\frac{\theta_1}{\theta_2}\rvert$	0.866***	0.789***	0.877***	0.876***	0.867***	0.845***	0.801***
	(0.217)	(0.217)	(0.218)	(0.217)	(0.219)	(0.23)	(0.219)

Note: Signif. codes: ***: 0.01, **: 0.05, *: 0.1. Clustered standard-errors at the municipality level in parentheses. All specifications include municipality and date-by-zone type fixed effects. Standard errors of the inferred work-to-home consumption substitution rate, $\lvert\frac{\theta_1}{\theta_2}\rvert$, are computed using the Delta Method.

Table 15: Sensitivity analysis: Transaction count and value responses to standardized telework shares

Sensitivity to Measurement Error: Alternative Telework Specifications. A possible concern in our empirical framework relates to potential measurement error in our telework variables, which could systematically bias our estimates of θ_1 and θ_2. This sensitivity analysis is particularly crucial because our telework measures are constructed rather than directly observed, making them potentially susceptible to various sources of measurement error. Such errors could arise from imperfect data collection, aggregation procedures, or the inherent complexity of capturing telework patterns across diverse geographic and temporal contexts. To comprehensively assess the robustness of our findings to these measurement challenges, we implement two distinct approaches that intentionally introduce varying degrees of measurement error into our telework variables.

First approach: Spatial Heterogeneity in Telework Measurement. Our first sensitivity test leverages the natural heterogeneity in work-from-home patterns across different municipal classifications. We construct alternative telework measures that exploit the differential telework intensities observed between urban core municipalities and commuting zone municipalities (see columns 2 and 3 of Table 1). This approach creates variation in measurement precision by utilizing zone-specific telework propensities, thereby allowing us to evaluate how our estimates respond to different levels of measurement accuracy across spatial contexts.

The results of this spatial heterogeneity test are presented in Table 16. We construct telework measures using zone-specific estimates $\widehat{\beta_{gt}}$, representing the share of teleworkers working from home in zone group g on day t. The resulting telework variables are calculated as: $\mathrm{RT}_{it}^{(\mathcal{H})} = \widehat{\beta_{g(i)t}} \frac{\sum_{jk} \tau_{kg(i)} \mathrm{Workers}_{ijk}}{\mathrm{Workers}_i^{(\mathcal{H})}}$ and $\mathrm{RT}_{jt}^{(\mathcal{W})} = \frac{\sum_i \widehat{\beta_{g(i)t}} \sum_k \tau_{kg(i)} \mathrm{Workers}_{ijk}}{\mathrm{Workers}_j^{(\mathcal{W})}}$. The estimated coefficients remain remarkably consistent with our baseline findings, demonstrating similar magnitudes and significance levels. The work-to-home substitution rates also show stability across this alternative specification, providing initial evidence that our results are robust to spatial measurement heterogeneity.

	Transaction count			Transaction value		
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{RT}^{(\mathcal{H})}_{\widehat{\beta_{gt}}}$	0.81***	0.67***	0.68***	0.73***	0.73**	0.73***
	(0.19)	(0.21)	(0.21)	(0.24)	(0.28)	(0.28)
$\text{RT}^{(\mathcal{W})}_{\widehat{\beta_{gt}}}$	-1.32***	-1.35***	-1.33***	-0.98***	-1.09***	-1.07***
	(0.35)	(0.36)	(0.36)	(0.35)	(0.37)	(0.36)
$\text{PT}^{(\mathcal{H})}$		1.14	1.14		0.17	0.18
		(1.16)	(1.15)		(1.14)	(1.14)
$\text{PT}^{(\mathcal{W})}$		1.82**	1.84**		3.26***	3.27***
		(0.79)	(0.79)		(0.81)	(0.80)
Rain			-0.0092**			-0.0070
			(0.0043)			(0.0050)
Public transp. disrupt.			0.0084			0.0060
			(0.0070)			(0.0084)
Inferred work-to-home consumption substitution rate						
$\lvert\frac{\theta_1}{\theta_2}\rvert$	0.6141***	0.4986***	0.5092***	0.7451***	0.6675***	0.6795***
	(0.1734)	(0.1536)	(0.1547)	(0.2478)	(0.2278)	(0.2317)
Fit statistics						
Observations	10,640	10,640	10,640	10,640	10,640	10,640
BIC	166,967.4	166,630.9	166,542.9	5,442,124.2	5,413,060.4	5,411,006.4

Note: Signif. codes: ***: 0.01, **: 0.05, *: 0.1. Clustered standard-errors at the municipality level in parentheses. All specifications include municipality and date-by-zone type fixed effects. Standard errors of the inferred work-to-home consumption substitution rate, $\lvert\frac{\theta_1}{\theta_2}\rvert$, are computed using the Delta Method.

Table 16: Transaction count and value responses to alternative telework shares (using $\widehat{\beta_{gt}}$)

Second Approach: Controlled Measurement Error Introduction. To more systematically evaluate sensitivity to measurement error, we implement a second approach that explicitly introduces varying levels of measurement error into our telework variables. This method computes daily telework rates β_{it} and inactive individual shares α_i at the finer Iris geographic level, while imposing the constraint that weekly telework sums match survey-reported averages. Section E details the methodology. The resulting telework variables are calculated as: $\text{RT}^{(\mathcal{H})}_{it} = \widehat{\beta_{it}} \frac{\sum_{jk} \tau_{kg(i)} \text{Workers}_{ijk}}{\text{Workers}^{(\mathcal{H})}_i}$ and $\text{RT}^{(\mathcal{W})}_{jt} = \frac{\sum_i \widehat{\beta_{it}} \sum_k \tau_{kg(i)} \text{Workers}_{ijk}}{\text{Workers}^{(\mathcal{W})}_j}$. While this finer geographic resolution potentially introduces additional estimation noise, it provides a valuable test of how our results respond to increased measurement error.

Table 17 presents the results of this controlled measurement error test. We compare telework effects using alternative measures with systematically varying levels of measurement error: $\text{RT}^{(\mathcal{H})}_{\text{scaled } \beta^{(1)}}$ and $\text{RT}^{(\mathcal{W})}_{\text{scaled } \beta^{(1)}}$ contain higher measurement error than $\text{RT}^{(\mathcal{H})}_{\text{scaled } \beta^{(2)}}$ and $\text{RT}^{(\mathcal{W})}_{\text{scaled } \beta^{(2)}}$. As expected, we observe that higher measurement error brings the estimated coefficients closer to zero, though they maintain their expected signs and remain statistically significant. Importantly, we find that the work-to-home consumption substitution rate systematically decreases as measurement error increases, with the most precise measures yielding substitution rates of 0.276-0.279 and the noisier measures yielding rates of 0.162-0.184. This pattern confirms that our baseline estimates represent a conservative lower bound, as any measurement error would tend to attenuate our estimated effects.

These sensitivity analyses provide critical evidence regarding the robustness of our findings to measurement error. The consistency of our coefficient signs and the systematic relationship between measurement error and effect size attenuation demonstrate that our baseline results are not artifacts of measurement precision. Rather, they suggest that our core findings are conservative estimates that would likely be stronger with more precise measurement. This robustness to alternative measurement specifications significantly strengthens the credibility of our empirical conclusions.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Transaction count						
$\text{RT}^{(\mathcal{H})}_{\text{scaled } \beta^{(1)}}$	0.14	0.15	0.15*			
	(0.10)	(0.09)	(0.09)			
$\text{RT}^{(\mathcal{W})}_{\text{scaled } \beta^{(1)}}$	-0.28	-0.44*	-0.42*			
	(0.26)	(0.26)	(0.26)			
$\text{RT}^{(\mathcal{H})}_{\text{scaled } \beta^{(2)}}$				0.20**	0.22**	0.23**
				(0.10)	(0.10)	(0.10)
$\text{RT}^{(\mathcal{W})}_{\text{scaled } \beta^{(2)}}$				-0.22	-0.41	-0.39
				(0.30)	(0.31)	(0.30)
$\text{PT}^{(\mathcal{H})}$		2.28**	2.27**		2.05*	2.04*
		(1.10)	(1.08)		(1.10)	(1.09)
$\text{PT}^{(\mathcal{W})}$		1.39*	1.42*		1.52**	1.55**
		(0.75)	(0.75)		(0.75)	(0.75)
Rain			-0.0097**			-0.0101**
			(0.0045)			(0.0046)
Public transp. disrupt.			0.0095			0.0097
			(0.0070)			(0.0070)
Inferred work-to-home consumption substitution rate						
$\lvert\frac{\theta_1}{\theta_2}\rvert$	0.1993***	0.1788**	0.1839**	0.2457***	0.2251***	0.2311***
	(0.0674)	(0.0734)	(0.0751)	(0.0612)	(0.0609)	(0.0626)
Fit statistics						
Observations	10,640	10,640	10,640	10,640	10,640	10,640
BIC	167,625.9	167,103.9	166,995.7	167,536.3	167,047.1	166,931.6
Panel B: Transaction value						
$\text{RT}^{(\mathcal{H})}_{\text{scaled } \beta^{(1)}}$	0.13	0.10	0.10			
	(0.10)	(0.11)	(0.11)			
$\text{RT}^{(\mathcal{W})}_{\text{scaled } \beta^{(1)}}$	-0.69***	-0.61***	-0.59***			
	(0.18)	(0.18)	(0.18)			
$\text{RT}^{(\mathcal{H})}_{\text{scaled } \beta^{(2)}}$				0.23**	0.21*	0.20*
				(0.11)	(0.11)	(0.11)
$\text{RT}^{(\mathcal{W})}_{\text{scaled } \beta^{(2)}}$				-0.85***	-0.76***	-0.72***
				(0.26)	(0.26)	(0.26)
$\text{PT}^{(\mathcal{H})}$		2.05**	2.08**		2.01**	2.04**
		(0.81)	(0.81)		(0.80)	(0.81)
$\text{PT}^{(\mathcal{W})}$		2.44***	2.47***		2.57***	2.61***
		(0.78)	(0.78)		(0.79)	(0.78)
Rain			-0.0098**			-0.0112**
			(0.0046)			(0.0046)
Public transp. disrupt.			0.0041			0.0036
			(0.0075)			(0.0073)
Inferred work-to-home consumption substitution rate						
$\lvert\frac{\theta_1}{\theta_2}\rvert$	0.1816*	0.1617	0.1673	0.2760**	0.2692*	0.2799*
	(0.1217)	(0.1552)	(0.1601)	(0.1293)	(0.1428)	(0.1496)
Fit statistics						
Observations	10,640	10,640	10,640	10,640	10,640	10,640
BIC	5,824,375.8	5,779,402.1	5,775,816.2	5,834,314.6	5,787,286.3	5,782,826.5

Note: Signif. codes: ***: 0.01, **: 0.05, *: 0.1. Clustered standard-errors at the municipality level in parentheses. All specifications include municipality and date fixed effects. Standard errors of the inferred work-to-home consumption substitution rate, $\lvert\frac{\theta_1}{\theta_2}\rvert$, are computed using the Delta Method.

Table 17: Sensitivity to measurement error: Transaction count and value responses to alternative telework specifications

Systematic Sensitivity Analysis: Quantifying Measurement Error Effects. Another critical component of our robustness framework involves evaluating how measurement error in our telework variables affects our estimated coefficients. This analysis is particularly important because our telework shares $\mathrm{RT}^{(\mathcal{H})}$ and $\mathrm{RT}^{(\mathcal{W})}$ are constructed variables rather than directly observed measures, making them potentially susceptible to measurement imperfections that could bias our estimates. By explicitly introducing and controlling for varying levels of measurement error, we can rigorously assess the sensitivity of our findings to potential data inaccuracies and determine whether our results are robust to different degrees of measurement precision.

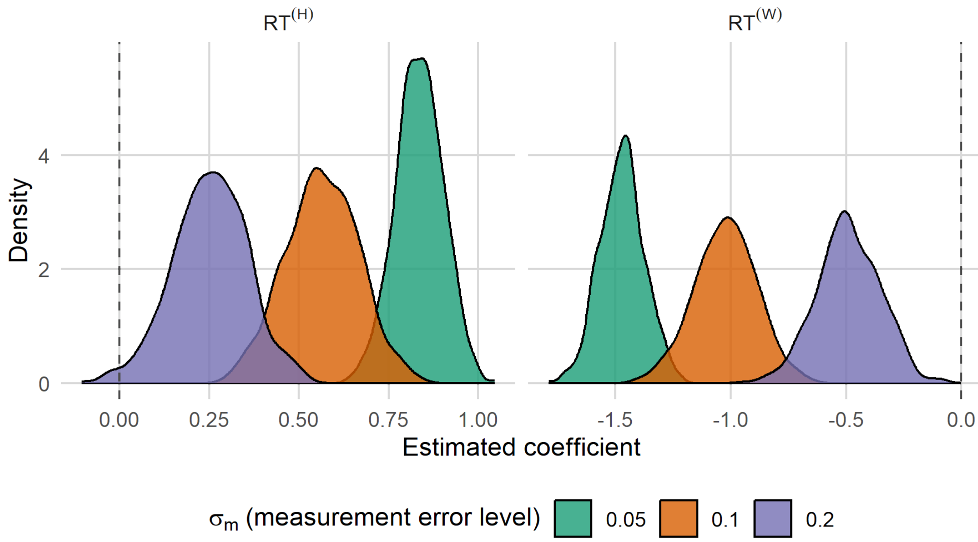
To quantitatively evaluate this sensitivity, we implement a controlled simulation approach that systematically introduces normally distributed random noise to our telework variables. For each variable, we generate measurement error proportional to specified error levels (σ_m) and create simulated variables according to: $\widetilde{\mathrm{RT}}_{it}^{(H)} = \mathrm{RT}_{it}^{(H)} + \varepsilon_{it}, \quad \varepsilon_{it} \sim \mathcal{N}\Big(0, \sigma_m\,\mathrm{sd}(\mathrm{RT}_{it}^{(H)})\Big)$. We repeat this procedure for three distinct error levels ($\sigma_m = \{0.05, 0.1, 0.2\}$) and across 500 iterations to obtain the empirical distribution of estimated coefficients for each error level. This approach allows us to systematically examine how increasing measurement error affects our parameter estimates.

Figure 12 presents the results of our measurement error simulation analysis, revealing a clear systematic pattern:

- For $\mathrm{RT}^{(\mathcal{H})}$, the mean coefficient decreases from 0.836 ($\sigma_m = 0.05$) to 0.252 ($\sigma_m = 0.20$).
- For $\mathrm{RT}^{(\mathcal{W})}$, the mean coefficient decreases in absolute value from -1.47 ($\sigma_m = 0.05$) to -0.490 ($\sigma_m = 0.20$).
- Standard deviations increase with higher error levels, reflecting greater estimation uncertainty.

The systematic attenuation of coefficients with increasing measurement error provides several important insights. First, all coefficients maintain their expected signs across all error levels, indicating that the fundamental relationships we identify are robust to measurement imperfections. Second, the attenuation pattern suggests our baseline estimates represent conservative lower bounds, as measurement error tends to bias estimates toward zero rather than inflate them. Third, coefficients remain statistically significant even at the highest error level ($\sigma_m = 0.20$), providing strong evidence for the robustness of our core findings.

This systematic sensitivity analysis demonstrates that while measurement error affects the magnitude of our estimates, it does not alter their fundamental direction or statistical significance. These findings significantly strengthen the credibility of our empirical conclusions by showing their resilience to one of the most common challenges in applied econometric analysis.



Note: This figure presents the empirical distribution of estimated coefficients from 500 simulations at three measurement error levels ($\sigma_m = 0.05, 0.10, 0.20$). For each simulation, normally distributed noise proportional to σ_m was added to the original telework variables, and the Poisson transaction model was re-estimated. The distributions show systematic attenuation of coefficients as measurement error increases, with mean values and standard deviations reported for each error level.

Figure 12: Impact of measurement error on estimated coefficients for $\mathrm{RT}^{(\mathcal{H})}$ and $\mathrm{RT}^{(\mathcal{W})}$

C.2.3 Causal Identification Strategies

Finally, to strengthen the causal interpretation of our findings and address potential threats to valid inference, we implement identification strategies that go beyond our baseline specifications. These approaches are particularly crucial given two fundamental challenges in our empirical framework: (1) potential endogeneity arising from unobserved confounders that may simultaneously affect telework patterns and local consumption, and (2) measurement error in our constructed telework variables that could bias our estimates. By employing instrumental variable techniques and alternative identification methods, we can more confidently establish the causal nature of the relationships we observe and assess the robustness of our findings to different identification approaches.

Instrumental Variable Approach To mitigate the potential bias from measurement error, we implement an instrumental variable (IV) strategy. This requires identifying instruments that are strongly correlated with the mismeasured explanatory variables but uncorrelated with the error term in the regression model. In the context of PPML estimation, we adopt a two-stage control function approach (Wooldridge, 2015), also called 2-Stage Residual Inclusion (2SRI). In the first stage, each mismeasured regressor is regressed on its instruments and other controls, and the residuals are saved. In the second stage, the original PPML regression is re-estimated, including the residuals from the first stage as additional covariates. This control function corrects for the endogeneity introduced by measurement error, restoring consistency of the PPML estimates. This strategy is particularly useful in nonlinear models like PPML where standard IV techniques cannot be applied directly, and it allows us to account for both measurement error and potential omitted variable bias.

The instruments follow a shift-share design to minimize correlation with local consumption and isolate exogenous variation in telework. The share component combines pre-COVID telework propensities by occupation (τ_k) from 2017, with pre-COVID residence-workplace-occupation workers matrix from 1999, 2010 and 2015 population census respectively - resulting in the creation of 3 different instruments for each telework measure. The daily shift component captures deviations in 2022 daily working from home rates ($\widehat{\beta}_t$) from daily part-time day-off rates of executives ($\gamma_{k=\text{executives},t}$). It captures the extent to which telework on a given day exceeds expected levels based on a baseline group, acting as a proxy for unanticipated shifts in home presence. This variation is plausibly unrelated to daily consumption, making it a valuable source of exogenous variation to identify causal effects. The instrumental variables are computed as follows:

$$\mathrm{IV}_{it}^{(\mathcal{H})} = 100 \cdot \left(\widehat{\beta}_t - \gamma_{k=\text{executives},t}\right) \cdot \frac{\sum_{jk} \tau_{k,2017} \text{Workers}_{ijk,1999}}{\text{Workers}_{1999}^{(\mathcal{H})}} \tag{10}$$

$$\mathrm{IV}_{jt}^{(\mathcal{W})} = 100 \cdot \left(\widehat{\beta}_t - \gamma_{k=\text{executives},t}\right) \cdot \frac{\sum_{ik} \tau_{k,2017} \text{Workers}_{ijk,1999}}{\text{Workers}_{1999}^{(\mathcal{W})}} \tag{11}$$

Tables 18–20 report the 2SRI IV estimation results for the effect of telework on transaction counts and values, respectively. Columns 5 and 8 present the baseline Poisson models estimated on a restricted sample of municipalities, excluding those that were merged or split between 2015 and 2021. The estimated coefficients remain broadly stable, showing slightly higher effects for both $\mathrm{RT}^{(\mathcal{H})}$ and $\mathrm{RT}^{(\mathcal{W})}$ when using the 1999 instruments, and slightly lower effects with the 2010-2015 instruments. All effects are highly significant (see Figures 13 and 14 for bootstrapped confidence intervals based on 1,000 iterations). However, the moderate significance of the control function terms ($\text{Residuals}^{(\mathcal{H})}$ and $\text{Residuals}^{(\mathcal{W})}$), particularly in the transaction value specifications, suggests limited evidence of endogeneity.

Columns 3 and 4 report the first-stage regressions, where the instruments significantly predict both telework variables, with moderate within R^2 values. Columns 1 and 2 confirm instrument relevance through partial regressions (instruments and fixed effects only), with low but significant Wald statistics. Column 7 and 10 presents a redundancy test showing that, conditional on the endogenous regressors, the instruments have no additional explanatory power (coefficients are not statistically different from zero), supporting their validity in providing independent variation.

Overall, the IV estimates confirm the main finding: telework induced presence at home increases local consumption, whereas telework induced absence from workplace reduces it. The implied work-to-home consumption substitution rate decreases from 0.66 in the baseline to 0.33-0.53 in the IV specification for transaction counts, and from 0.78 to 0.40-0.66 for transaction value. The stability of our results across different identification strategies, combined with the systematic assessment of potential endogeneity, significantly enhances the credibility of our causal interpretations regarding the impact of telework on local consumption patterns.

Dependent Variables:	$RT^{(\mathcal{H})}$	$RT^{(\mathcal{W})}$	$RT^{(\mathcal{H})}$	$RT^{(\mathcal{W})}$		Transaction count			Transaction value	
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Relevance test		First-stage		Baseline	Second-stage	Redundancy	Baseline	Second-stage	Redundancy
	OLS	OLS	OLS	OLS	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson
Variables										
$IV^{(\mathcal{H})}_{1999}$	3.90***	1.00*	3.52***	-0.735			-0.429			0.778
	(1.11)	(0.534)	(1.03)	(0.583)			(1.61)			(1.84)
$IV^{(\mathcal{W})}_{1999}$	-2.42***	0.342	-2.55***	1.42***			-0.595			-1.60
	(0.754)	(0.392)	(0.738)	(0.492)			(1.08)			(1.19)
$RT^{(\mathcal{H})}$				0.445***	1.15***	1.25***	1.13***	1.06***	1.44***	0.944***
				(0.045)	(0.226)	(0.357)	(0.259)	(0.269)	(0.412)	(0.283)
$RT^{(\mathcal{W})}$			0.386***		-1.74***	-2.34***	-1.45***	-1.36***	-2.19***	-1.04***
			(0.044)		(0.383)	(0.411)	(0.344)	(0.391)	(0.640)	(0.366)
$Residuals^{(\mathcal{H})}$						0.336			0.022	
						(0.499)			(0.616)	
$Residuals^{(\mathcal{W})}$						1.02**			1.16	
						(0.424)			(0.777)	
Fit statistics										
Observations	10,600	10,600	10,600	10,600	10,600	10,600	10,600	10,600	10,600	10,600
BIC	-70,030.1	-68,517.3	-72,020.7	-70,507.8	166,527.7	166,376.4	166,376.4	5,428,850.1	5,418,952.6	5,418,952.6
R^2	0.96932	0.95623	0.97459	0.96375						
Within R^2	0.04086	0.01824	0.20576	0.18704						
Wald stat	6.2	9.1	30.8	40.1						

Note: Signif. codes: ***: 0.01, **: 0.05, *: 0.1. Clustered standard-errors at the municipality level in parentheses. All specifications include municipality and date-by-zone type fixed effects. The table presents a series of estimations examining the relationship between teleworking intensity and local consumption outcomes. Columns (1)–(2) report OLS relevance tests, verifying the correlation between telework indicators and the shift-share instruments constructed from the 1999 residence–workplace–occupation matrix of the population census. Columns (3)–(4) display the first-stage regressions. Columns (5)–(7) and (8)–(10) present Poisson estimations for the number and total value of transactions at the municipal level, respectively, including baseline models, second-stage models incorporating the first-stage residual (control function), and redundancy tests to assess the exogeneity of the instruments.

Table 18: 2SRI results, 1999 instruments

Dependent Variables:	$RT^{(\mathcal{H})}$	$RT^{(\mathcal{W})}$	$RT^{(\mathcal{H})}$	$RT^{(\mathcal{W})}$		Transaction count			Transaction value	
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Relevance test		First-stage		Baseline	Second-stage	Redundancy	Baseline	Second-stage	Redundancy
	OLS	OLS	OLS	OLS	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson
$IV_{2010}^{(\mathcal{H})}$	3.19***	-0.223	3.27***	-1.68***			-0.834			-0.297
	(0.791)	(0.560)	(0.699)	(0.536)			(1.27)			(1.87)
$IV_{2010}^{(\mathcal{W})}$	-2.16***	0.969**	-2.54***	1.96***			-0.086			-0.519
	(0.536)	(0.472)	(0.495)	(0.470)			(1.03)			(1.37)
$RT^{(\mathcal{H})}$				0.457***	1.15***	0.837***	1.15***	1.06***	0.849*	1.00***
				(0.045)	(0.226)	(0.316)	(0.269)	(0.269)	(0.510)	(0.306)
$RT^{(\mathcal{W})}$			0.398***		-1.74***	-2.27***	-1.48***	-1.36***	-2.00***	-1.12***
			(0.045)		(0.383)	(0.399)	(0.354)	(0.391)	(0.589)	(0.384)
$\text{Residuals}^{(\mathcal{H})}$						0.834*			0.681	
						(0.451)			(0.800)	
$\text{Residuals}^{(\mathcal{W})}$						1.13**			1.15	
						(0.445)			(0.777)	
Fit statistics										
Observations	10,600	10,600	10,600	10,600	10,600	10,600	10,600	10,600	10,600	10,600
BIC	-70,004.4	-68,545.9	-72,126.1	-70,667.6	166,527.7	166,378.0	166,378.0	5,428,850.1	5,423,588.8	5,423,588.8
R^2	0.96924	0.95635	0.97484	0.96430						
Within R^2	0.03852	0.02089	0.21362	0.19920						
Wald stat	8.6	7.6	33.3	38.8						

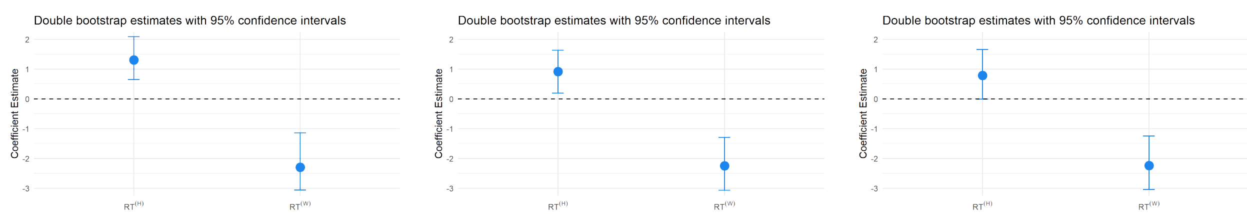
Note: Signif. codes: ***: 0.01, **: 0.05, *: 0.1. Clustered standard-errors at the municipality level in parentheses. All specifications include municipality and date-by-zone type fixed effects. The table presents a series of estimations examining the relationship between teleworking intensity and local consumption outcomes. Columns (1)–(2) report OLS relevance tests, verifying the correlation between telework indicators and the shift-share instruments constructed from the 2010 residence–workplace–occupation matrix of the population census. Columns (3)–(4) display the first-stage regressions. Columns (5)–(7) and (8)–(10) present Poisson estimations for the number and total value of transactions at the municipal level, respectively, including baseline models, second-stage models incorporating the first-stage residual (control function), and redundancy tests to assess the exogeneity of the instruments.

Table 19: 2SRI results, 2010 instruments

Dependent Variables:	$RT^{(\mathcal{H})}$	$RT^{(\mathcal{W})}$	$RT^{(\mathcal{H})}$	$RT^{(\mathcal{W})}$		Transaction count			Transaction value	
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Relevance test		First-stage		Baseline	Second-stage	Redundancy	Baseline	Second-stage	Redundancy
	OLS	OLS	OLS	OLS	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson
$IV^{(\mathcal{H})}_{2015}$	2.41***	-0.122	2.46***	-1.21**			-0.938			-0.590
	(0.697)	(0.499)	(0.632)	(0.494)			(0.890)			(1.43)
$IV^{(\mathcal{W})}_{2015}$	-1.58***	0.796*	-1.89***	1.51***			0.066			-0.161
	(0.469)	(0.454)	(0.478)	(0.492)			(0.694)			(0.963)
$RT^{(\mathcal{H})}$				0.451***	1.15***	0.737**	1.16***	1.06***	0.760	1.04***
				(0.045)	(0.226)	(0.337)	(0.242)	(0.269)	(0.557)	(0.283)
$RT^{(\mathcal{W})}$			0.396***		-1.74***	-2.25***	-1.49***	-1.36***	-1.94***	-1.18***
			(0.045)		(0.383)	(0.394)	(0.335)	(0.391)	(0.566)	(0.365)
$Residuals^{(\mathcal{H})}$						0.940**			0.765	
						(0.443)			(0.831)	
$Residuals^{(\mathcal{W})}$						1.14***			1.07	
						(0.426)			(0.753)	
Fit statistics										
Observations	10,600	10,600	10,600	10,600	10,600	10,600	10,600	10,600	10,600	10,600
BIC	-69,905.7	-68,541.0	-71,980.8	-70,616.1	166,527.7	166,371.7	166,371.7	5,428,850.1	5,424,426.8	5,424,426.8
R^2	0.96895	0.95633	0.97450	0.96412						
Within R^2	0.02953	0.02043	0.20277	0.19530						
Wald stat	6.2	6.4	30.6	38.2						

Note: Signif. codes: ***: 0.01, **: 0.05, *: 0.1. Clustered standard-errors at the municipality level in parentheses. All specifications include municipality and date-by-zone type fixed effects. The table presents a series of estimations examining the relationship between teleworking intensity and local consumption outcomes. Columns (1)–(2) report OLS relevance tests, verifying the correlation between telework indicators and the shift-share instruments constructed from the 2015 residence–workplace–occupation matrix of the population census. Columns (3)–(4) display the first-stage regressions. Columns (5)–(7) and (8)–(10) present Poisson estimations for the number and total value of transactions at the municipal level, respectively, including baseline models, second-stage models incorporating the first-stage residual (control function), and redundancy tests to assess the exogeneity of the instruments.

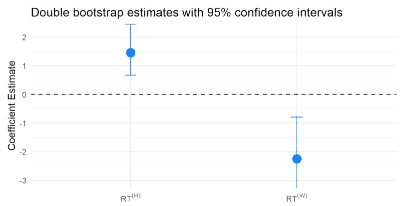
Table 20: 2SRI results, 2015 instruments



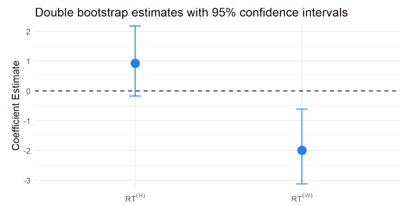
(a) 1999 Instruments (b) 2010 Instruments (c) 2015 Instruments

Note: These panels present the estimated effects of a one-percentage-point increase in $RT^{(\mathcal{H})}$ and $RT^{(\mathcal{W})}$ on transaction count, along with 95% confidence intervals, using a double bootstrap procedure. The procedure accounts for uncertainty in both the first-stage and second-stage of the 2SRI estimation, using instruments from 1999, 2010, and 2015. Specifically, the double bootstrap involves 1,000 resamplings with replacement of municipalities, re-estimating the entire 2SRI procedure in each resample to regenerate the predicted telework variables. The 95% confidence intervals are then computed from the distribution of the bootstrapped estimates, using standard errors clustered at the municipality level. All specifications include municipality fixed effects and date-by-zone type fixed effects.

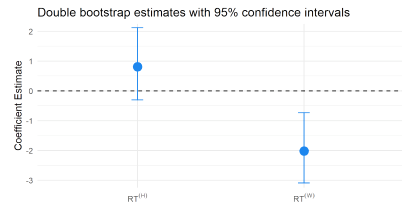
Figure 13: Bootstrapped 2SRI coefficients and confidence intervals for transaction counts by instrument year



(a) 1999 Instruments



(b) 2010 Instruments



(c) 2015 Instruments

Note: This figure presents the estimated effects of a one-percentage-point increase in $\mathrm{RT}^{(\mathcal{H})}$ and $\mathrm{RT}^{(\mathcal{W})}$ on transaction value, along with 95% confidence intervals, using a double bootstrap procedure. The procedure accounts for uncertainty in both the first-stage and second-stage of the 2SRI estimation, using instruments from 1999, 2010, and 2015. Specifically, the double bootstrap involves 1,000 resamplings with replacement of municipalities, re-estimating the entire 2SRI procedure in each resample to regenerate the predicted telework variables. The 95% confidence intervals are then computed from the distribution of the bootstrapped estimates, using standard errors clustered at the municipality level. All specifications include municipality fixed effects and date-by-zone type fixed effects.

Figure 14: Bootstrapped 2SRI coefficients and confidence intervals for transaction values by instrument year

Alternative Identification Strategy: Spatial Variation in Telework Exposure. Our main analysis in Section 4 estimates the causal impact of telework on local consumption using daily telework shares, which capture day-to-day fluctuations in telework adoption. To ensure the robustness of these findings, we adopt an alternative identification strategy that relies solely on spatial variation in telework exposure across municipalities. This approach tests whether our results are sensitive to the choice of identification strategy by using a simpler, time-invariant measure of telework potential. If both approaches yield consistent results, it suggests that our findings are not driven by the specific modeling of daily telework.

We estimate the following Poisson Maximum Likelihood regression model:

$$Y_{it} = \exp\left[\theta_1 \mathrm{TE}_i^{(\mathcal{H})} + \theta_2 \mathrm{TE}_i^{(\mathcal{W})} + \theta_3 \log(\mathrm{Pop}_i) + \theta_4 \log(\mathrm{Workers}_i) + \delta_g + \gamma_t + \epsilon_{it}\right]. \tag{12}$$

In this specification, the dependent variable Y_{it} denotes the number or total value of in-person transactions for municipality i on date t. The two main explanatory variables are $\mathrm{TE}_i^{(\mathcal{H})}$, which captures the potential for telework at the place of residence (interpreted as a proxy for increased home presence), and $\mathrm{TE}_i^{(\mathcal{W})}$, which captures the potential for telework at the place of work (interpreted as a proxy for reduced workplace attendance).

The model includes controls for standard demand-side determinants, namely the resident population and the total number of workers, as well as fixed effects for location types within the functional urban area (δ_g), which account for differences in local supply density and accessibility. Date fixed effects (γ_t) are included to capture temporal shocks and common trends unrelated to telework, allowing us to isolate the impact of telework on consumption-related outcomes.

The coefficient θ_1 can be interpreted as the semi-elasticity of transactions with respect to residential telework exposure: when multiplied by 100, it represents the percentage change in the dependent variable associated with a one percentage point increase in the share of residents who can telework. Similarly, θ_2 captures the effect of a one percentage point increase in telework potential at workplace locations, interpreted as reduced physical presence at these sites. We expect

θ_1 to be positive, reflecting increased local consumption, and θ_2 to be negative, indicating reduced demand in areas where workers are less physically present.

The results of this alternative specification are presented in Table 21. The coefficients for $\mathrm{TE}_i^{(\mathcal{H})}$ and $\mathrm{TE}_i^{(\mathcal{W})}$ are consistent with the main analysis, though with larger standard errors. The alternative identification strategy confirms the direction and qualitative nature of the main results. The larger standard errors in this specification highlight the trade-off between precision and robustness when using spatial variation instead of daily telework shares. Overall, this analysis reinforces confidence in the core findings of the study.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Transaction count							
Constant	3.62***	-1.19***					
	(0.463)	(0.376)					
$\mathrm{TE}^{(\mathcal{H})}$	4.10	2.36	2.36	2.36*			
	(3.47)	(1.51)	(1.51)	(1.29)			
$\mathrm{TE}^{(\mathcal{W})}$	19.3***	-3.97**	-3.97**	-4.17**			
	(3.06)	(1.90)	(1.90)	(2.11)			
log(Population)		0.105	0.105	0.119	0.106	0.125	
		(0.140)	(0.140)	(0.160)	(0.139)	(0.159)	
log(Workers)		0.991***	0.991***	0.948***	0.978***	0.936***	
		(0.124)	(0.124)	(0.125)	(0.121)	(0.120)	
$\mathrm{RT}^{(\mathcal{H})}$					3.92	3.96*	1.15***
					(2.55)	(2.12)	(0.226)
$\mathrm{RT}^{(\mathcal{W})}$					-6.35**	-6.95**	-1.74***
					(2.72)	(3.37)	(0.383)
Fixed-effects							
Date			✓		✓		
Date-zone type				✓		✓	✓
Municip							✓
Fit statistics							
Observations	10,680	10,680	10,680	10,680	10,680	10,680	10,640
BIC	28,989,209.6	4,588,981.3	4,447,077.4	4,152,586.6	4,460,116.1	4,167,541.0	166,692.0
Panel B: Transaction value							
Constant	7.63***	3.29***					
	(0.444)	(0.482)					
$\mathrm{TE}^{(\mathcal{H})}$	2.47	1.35	1.35	2.95*			
	(3.39)	(1.71)	(1.71)	(1.61)			
$\mathrm{TE}^{(\mathcal{W})}$	18.6***	-4.80**	-4.80**	-5.24**			
	(2.94)	(2.30)	(2.30)	(2.50)			
log(Population)		-0.022	-0.022	-0.031	-0.024	-0.022	
		(0.159)	(0.159)	(0.188)	(0.156)	(0.185)	
log(Workers)		1.07***	1.07***	1.06***	1.04***	1.04***	
		(0.139)	(0.139)	(0.143)	(0.133)	(0.136)	
$\mathrm{RT}^{(\mathcal{H})}$					1.98	4.84*	1.06***
					(2.85)	(2.63)	(0.269)
$\mathrm{RT}^{(\mathcal{W})}$					-6.85**	-8.53**	-1.36***
					(3.20)	(3.97)	(0.391)
Fixed-effects							
Date			✓		✓		
Date-zone type				✓		✓	✓
Municip							✓
Fit statistics							
Observations	10,680	10,680	10,680	10,680	10,680	10,680	10,640
BIC	1,078,909,817.5	238,542,019.9	228,926,338.3	210,077,249.1	230,532,892.5	211,143,747.9	5,434,198.5

Note: Signif. codes: ***: 0.01, **: 0.05, *: 0.1. Clustered standard-errors at the municipality level in parentheses.

Table 21: Spatial variation analysis: Transaction count and value responses to telework potential

C.3 Quantifying the Net Economic Impact of Telework

We now turn to quantifying the net economic impact of telework adoption. This section presents a comprehensive counterfactual analysis designed to address three critical policy-relevant questions, with results presented in Figures 15–22.

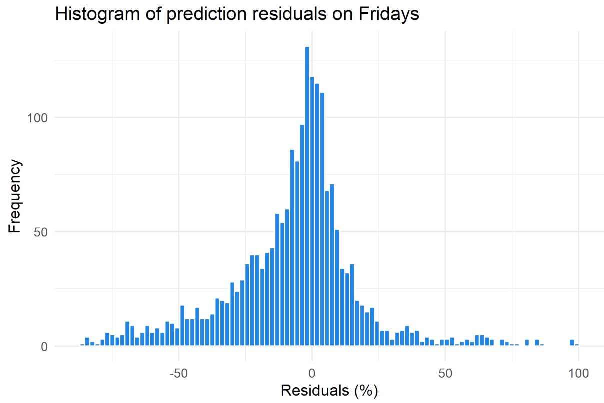
First, we examine the aggregate effect of telework on local economic activity when simultaneously considering both residential and workplace impacts. As illustrated in Figures 16–20, our analysis reveals the net balance between increased residential consumption and reduced workplace activity across different weekdays. These figures show the percentage change in both transaction counts and values, computed as $(\hat{y}_i - \hat{y}_i^0)/\hat{y}_i^0$, where $\hat{y}_i$ represents model-predicted values and $\hat{y}_i^0$ represents counterfactual predictions under a zero-telework scenario.

Second, we investigate how this net effect varies across different days of the week, reflecting the temporal heterogeneity in telework adoption patterns. Figure 15 demonstrates the model's predictive accuracy through the distribution of prediction errors, providing the foundation for our day-specific analyses. The patterns observed in Figures 16–20 correspond to documented variations in telework intensity across the workweek, with Friday typically showing the most pronounced effects due to higher telework adoption rates at the end of the workweek.

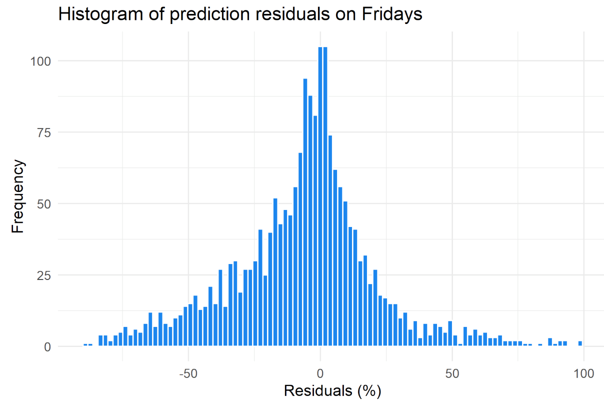
Third, we explore which municipalities benefit from telework adoption and which experience economic losses. Figure 21 analyzes this spatial heterogeneity by relating predicted transaction changes to key municipal characteristics. The spatial distribution of economic winners and losers across different zone groups within the functional urban area is further illustrated in Figure 22, which shows the percentage of municipalities experiencing declines in transaction values.

Our analytical approach integrates several complementary elements that build upon one another. The counterfactual simulation framework (Figure 15) demonstrates the model's predictive accuracy and provides the foundation for our subsequent analyses. The day-specific results (Figures 16–20) reveal important temporal patterns in telework impacts, while our spatial decomposition analysis (Figures 21 and 22) identifies systematic relationships between telework impacts and municipal characteristics.

This comprehensive, multi-faceted approach provides a complete understanding of telework's net economic impact. By combining temporal and spatial analyses with our counterfactual framework, we offer policy-makers nuanced insights into the heterogeneous economic consequences of telework adoption across different communities and time periods.



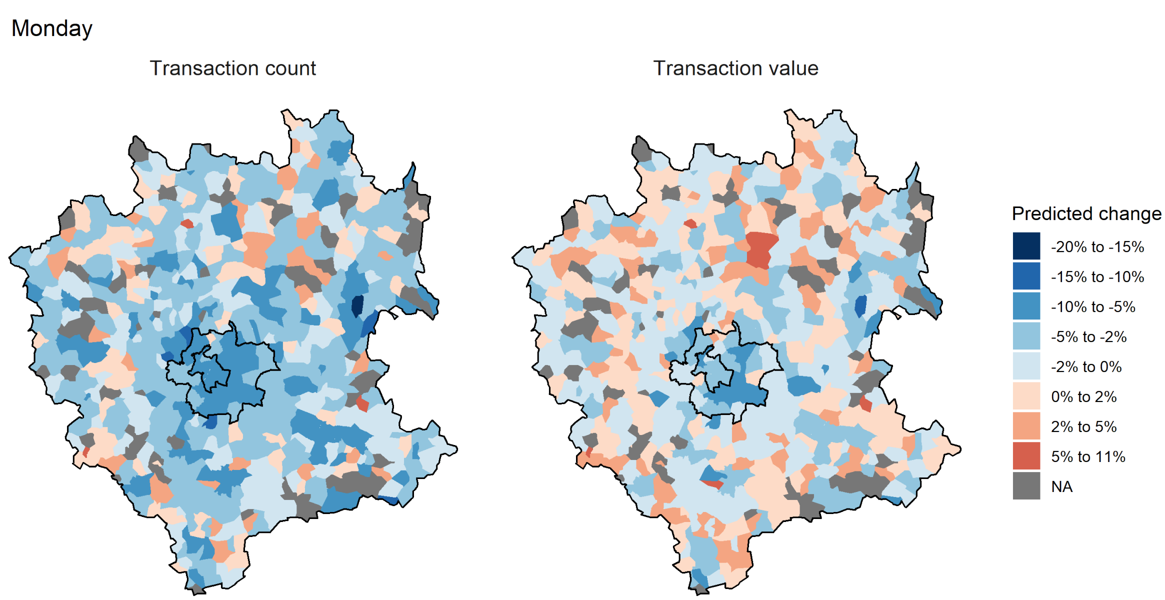
(a) Transaction count model



(b) Transaction value model

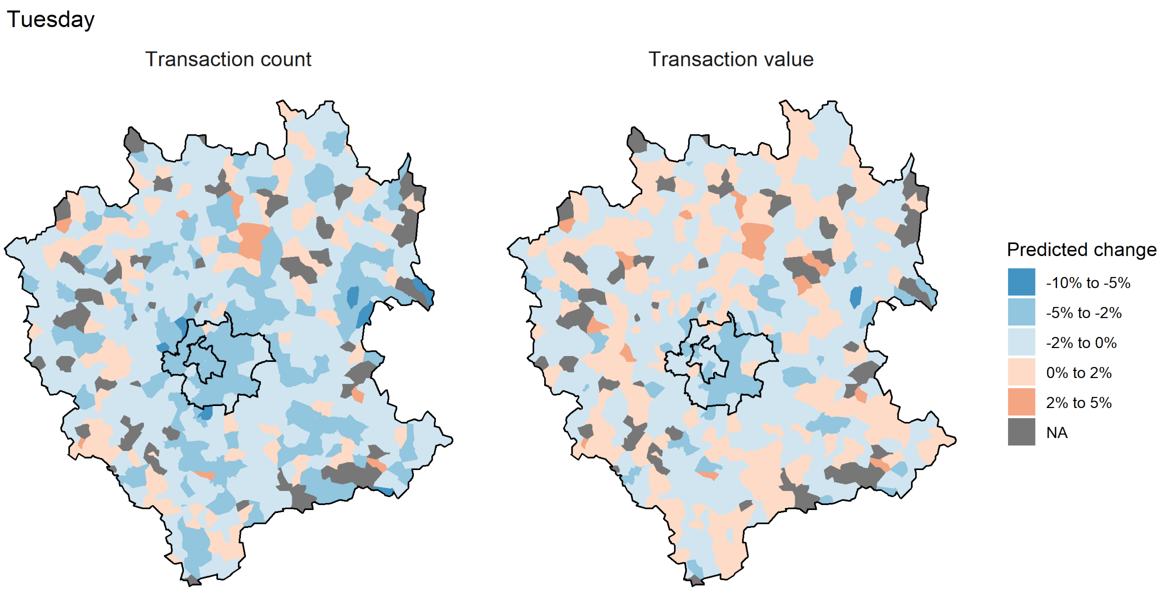
Note: This figure presents the distribution of the prediction error in percentage to Poisson Maximum Likelihood specifications, with the whole set of controls, and fixed effects for municipality and date-by-zone type.

Figure 15: Residuals distribution on Fridays



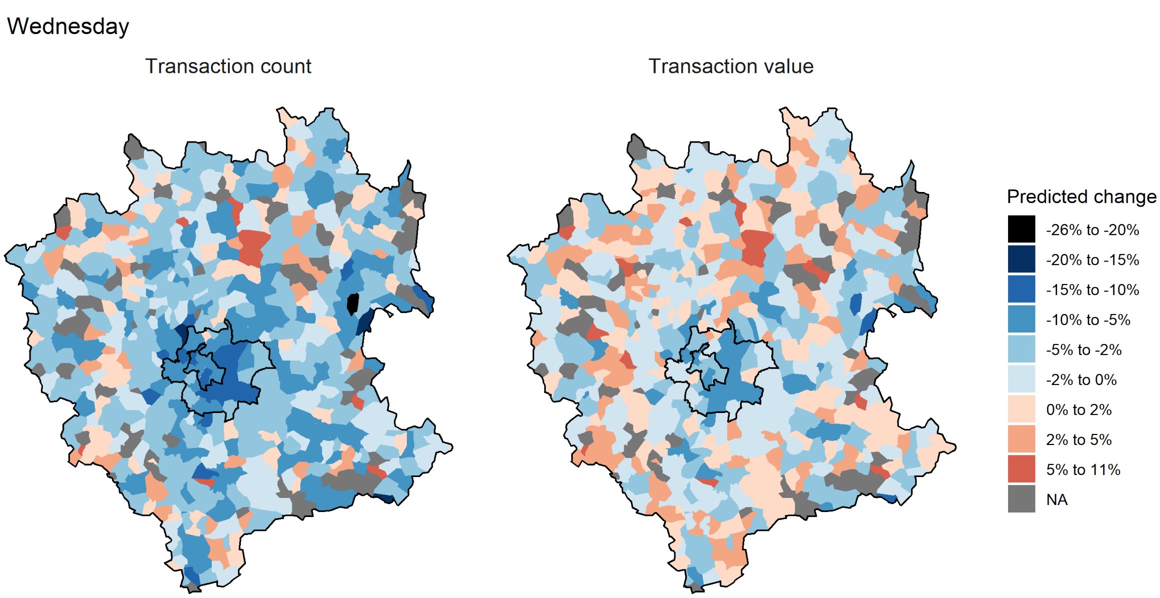
Note: The two figures show the average effect of telework on Mondays, measured as the percentage change in transaction count and transaction value, respectively. This is computed as $(\hat{y}_i - \hat{y}_i^0)/\hat{y}_i^0$, where $\hat{y}_i$ denotes the model-predicted values averaged over Mondays, and $\hat{y}_i^0$ denotes the counterfactual predicted values under a zero-telework scenario, also averaged over Mondays. The predictions are based on a model that includes municipality fixed effects, date-by-zone-type fixed effects, and the full set of control variables.

Figure 16: Average effect of telework on Monday



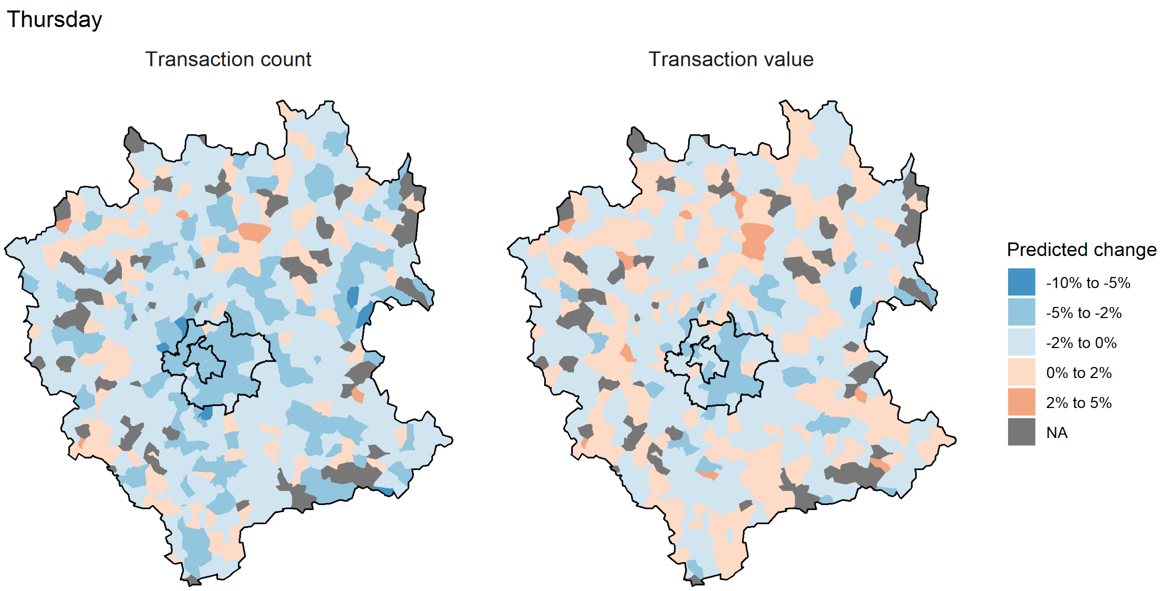
Note: The two figures show the average effect of telework on Tuesdays, measured as the percentage change in transaction count and transaction value, respectively. This is computed as $(\hat{y}_i - \hat{y}_i^0)/\hat{y}_i^0$, where $\hat{y}_i$ denotes the model-predicted values averaged over Tuesdays, and $\hat{y}_i^0$ denotes the counterfactual predicted values under a zero-telework scenario, also averaged over Tuesdays. The predictions are based on a model that includes municipality fixed effects, date-by-zone-type fixed effects, and the full set of control variables.

Figure 17: Average effect of telework on Tuesday



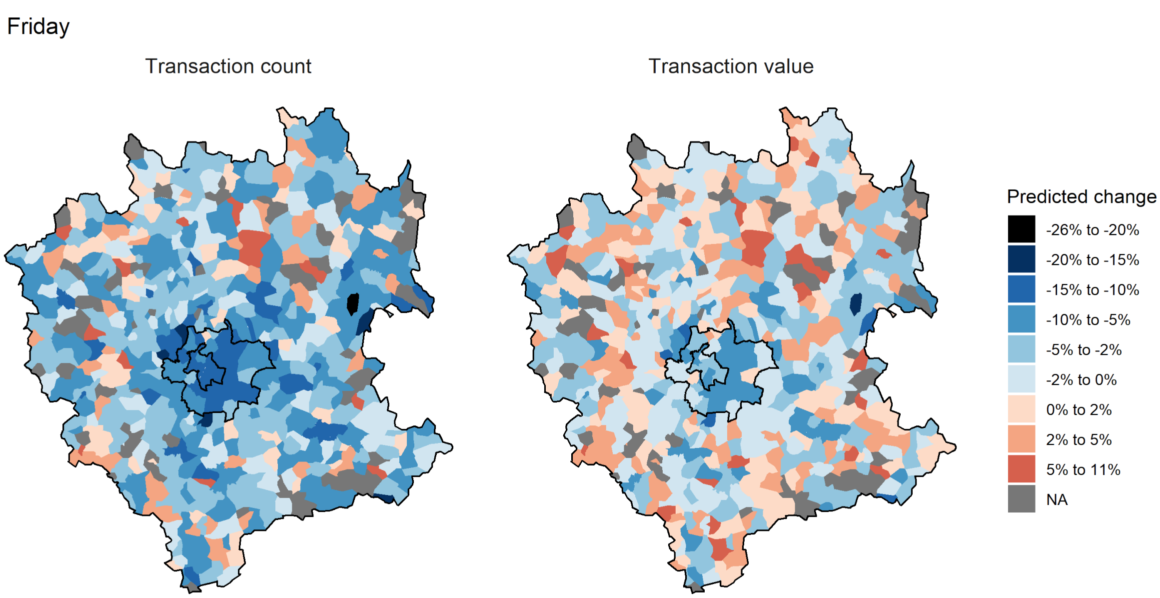
Note: The two figures show the average effect of telework on Wednesdays, measured as the percentage change in transaction count and transaction value, respectively. This is computed as $(\hat{y}_i - \hat{y}_i^0)/\hat{y}_i^0$, where $\hat{y}_i$ denotes the model-predicted values averaged over Wednesdays, and $\hat{y}_i^0$ denotes the counterfactual predicted values under a zero-telework scenario, also averaged over Wednesdays. The predictions are based on a model that includes municipality fixed effects, date-by-zone-type fixed effects, and the full set of control variables.

Figure 18: Average effect of telework on Wednesday



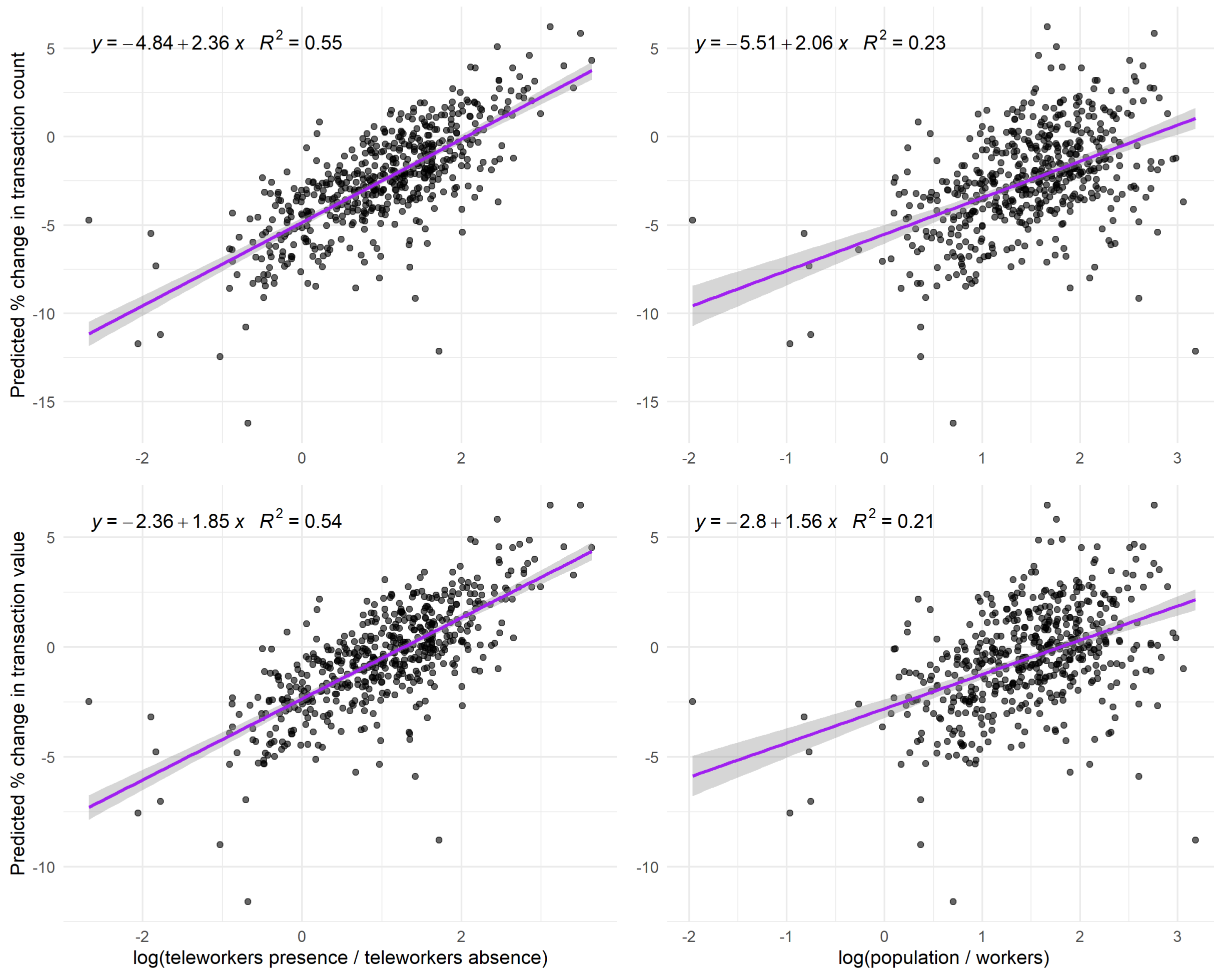
Note: The two figures show the average effect of telework on Thursdays, measured as the percentage change in transaction count and transaction value, respectively. This is computed as $(\hat{y}_i - \hat{y}_i^0)/\hat{y}_i^0$, where $\hat{y}_i$ denotes the model-predicted values averaged over Thurdays, and $\hat{y}_i^0$ denotes the counterfactual predicted values under a zero-telework scenario, also averaged over Thursdays. The predictions are based on a model that includes municipality fixed effects, date-by-zone-type fixed effects, and the full set of control variables.

Figure 19: Average effect of telework on Thursday



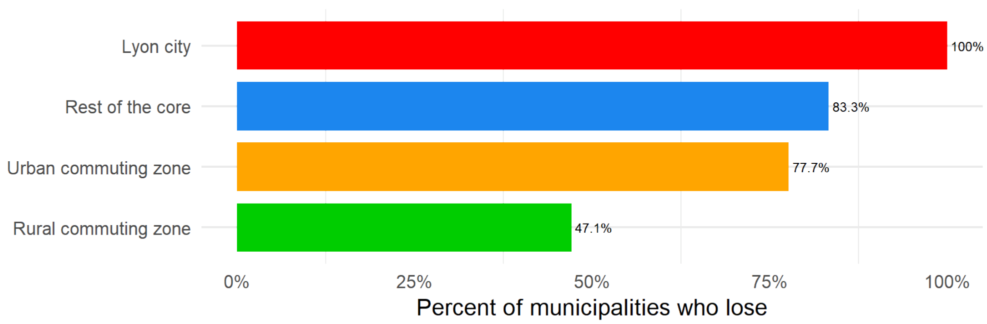
Note: The two figures show the average effect of telework on Fridays, measured as the percentage change in transaction count and transaction value, respectively. This is computed as $(\hat{y}_i - \hat{y}_i^0)/\hat{y}_i^0$, where $\hat{y}_i$ denotes the model-predicted values averaged over Fridays, and $\hat{y}_i^0$ denotes the counterfactual predicted values under a zero-telework scenario, also averaged over Fridays. The predictions are based on a model that includes municipality fixed effects, date-by-zone-type fixed effects, and the full set of control variables.

Figure 20: Average effect of telework on Friday



Note: The figures illustrate the relationship between the predicted percentage change in transactions resulting from telework and two municipal characteristics: (i) the ratio of resident teleworkers to employed teleworkers, and (ii) the ratio of total population to employed workers. The figures on the left show that municipalities with a higher ratio of resident teleworkers (those present at home) relative to employed teleworkers (those absent from the workplace) tend to experience larger predicted increases-or smaller declines-in transaction counts and values, consistent with the model's results. The figures on the right indicate that municipalities with a higher ratio of total population to employed workers generally exhibit larger predicted increases-or smaller declines- in transaction counts and values.

Figure 21: Predicted transaction change in relation to municipalities demographics



Note: The figure shows the percentage of municipalities within each zone group of Lyon FUA that are predicted to experience a decline in transaction values from telework.

Figure 22: Percent of municipalities who lose, per zone group within the FUA

C.4 Sectoral Heterogeneity in Telework Effects

This appendix extends our main analysis by examining how the economic impacts of telework vary across different economic sectors. Building upon the aggregate findings presented in Section 4, we investigate sector-specific responses to telework adoption, providing nuanced insights into the heterogeneous effects across various types of economic activities. This analysis is particularly important as different sectors likely exhibit distinct patterns of consumption response to changes in telework patterns, reflecting variations in consumer behavior, product characteristics, and operational structures.

C.4.1 Standardized Telework Shares

Our sectoral analysis begins by estimating the differential impacts of telework on seven key economic sectors: Restaurants, Food Retail, Bars and Drinks, General Retail, Clothing, Recreation, and Health. We employ standardized telework shares to ensure comparability across sectors with different baseline levels of telework adoption. Table 22 presents the estimated coefficients for both transaction counts and values, along with the inferred work-to-home consumption substitution rates for each sector. The results reveal substantial heterogeneity in sectoral responses to telework. The Bars and Drinks sector shows the strongest positive response to residential telework, with a coefficient of 0.132 for transaction counts and 0.141 for transaction values, suggesting that increased home presence significantly boosts consumption in this sector. This likely reflects the social nature of bar and drink consumption, where proximity to residential areas becomes particularly important. The Recreation sector also exhibits a strong positive response, though with wider confidence intervals due to greater variability in consumption patterns.

In contrast, sectors like General Retail and Clothing show more modest responses to residential telework, with coefficients closer to zero and in some cases not statistically significant. This pattern suggests that consumption in these sectors may be less sensitive to local presence and more influenced by other factors such as planned shopping trips or online alternatives. The workplace telework effects generally show the expected negative signs across sectors, though with varying magnitudes. The Restaurants sector exhibits the strongest negative workplace effect (-0.147 for counts, -0.138 for values), indicating that reduced workplace presence has particularly pronounced consequences for local restaurant consumption. This finding aligns with the social and convenience-oriented nature of restaurant visits during workdays. The inferred work-to-home consumption substitution rates vary substantially across sectors. Bars and Drinks show the highest substitution rate (1.575 for counts, 1.597 for values), suggesting that each percentage point increase in residential telework is associated with more than one and a half times that increase in local consumption. At the other end of the spectrum, the Health sector shows the lowest substitution rates (0.402 for counts, 0.578 for values), indicating more inelastic consumption patterns in response to telework changes.

	Restaurants (1)	Food (2)	Bars (3)	General (4)	Clothing (5)	Recreation (6)	Health (7)
Panel A: Transaction count							
$\text{RT}_{sd}^{(\mathcal{H})}$	0.044***	0.048***	0.132***	0.036*	0.015	0.134	0.009
	(0.016)	(0.009)	(0.047)	(0.019)	(0.030)	(0.125)	(0.010)
$\text{RT}_{sd}^{(\mathcal{W})}$	-0.147***	-0.053***	-0.084	-0.043**	-0.025	-0.198	-0.022*
	(0.027)	(0.015)	(0.057)	(0.021)	(0.034)	(0.142)	(0.012)
Fit statistics							
Observations	9,200	7,140	4,340	5,300	2,640	3,320	4,880
BIC	103,928.4	117,787.2	54,097.8	64,009.5	31,714.6	38,846.6	39,287.8
Inferred work-to-home consumption substitution rate							
$\lvert\frac{\theta_1}{\theta_2}\rvert$	0.299**	0.906***	1.575*	0.834**	0.596	0.675*	0.402
	(0.1)	(0.213)	(0.894)	(0.384)	(0.814)	(0.421)	(0.349)
Panel B: Transaction value							
$\text{RT}_{sd}^{(\mathcal{H})}$	0.052**	0.060***	0.141***	0.015	-0.009	0.114	0.016
	(0.024)	(0.013)	(0.048)	(0.022)	(0.033)	(0.073)	(0.015)
$\text{RT}_{sd}^{(\mathcal{W})}$	-0.138***	-0.047*	-0.088	-0.035*	-0.010	-0.199**	-0.028
	(0.034)	(0.024)	(0.056)	(0.019)	(0.031)	(0.093)	(0.023)
Fit statistics							
Observations	9,200	7,140	4,340	5,300	2,640	3,320	4,880
BIC	2,308,510.0	2,552,940.9	933,548.1	2,583,980.8	1,501,635.4	1,099,998.1	528,080.4
Inferred work-to-home consumption substitution rate							
$\lvert\frac{\theta_1}{\theta_2}\rvert$	0.374**	1.287**	1.597*	0.427	0.890	0.574*	0.578
	(0.134)	(0.614)	(0.854)	(0.546)	(5.293)	(0.312)	(0.470)

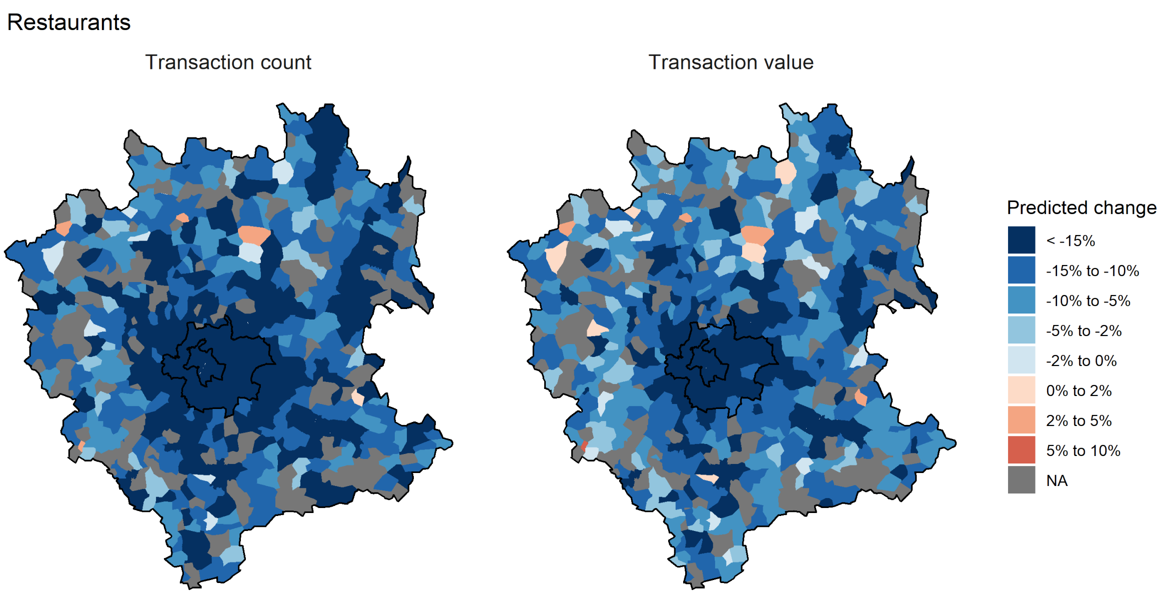
Note: Signif. codes: ***: 0.01, **: 0.05, *: 0.1. Clustered standard-errors at the municipality level in parentheses. All specifications include the whole set of controls, as well as municipality and date-by-zone type fixed effects. Standard errors of the inferred work-to-home consumption substitution rate, $\lvert\frac{\theta_1}{\theta_2}\rvert$, are computed using the Delta Method.

Table 22: Sectoral heterogeneity in transaction count and value responses to standardized telework share

C.4.2 Net Effects of Telework by Sector

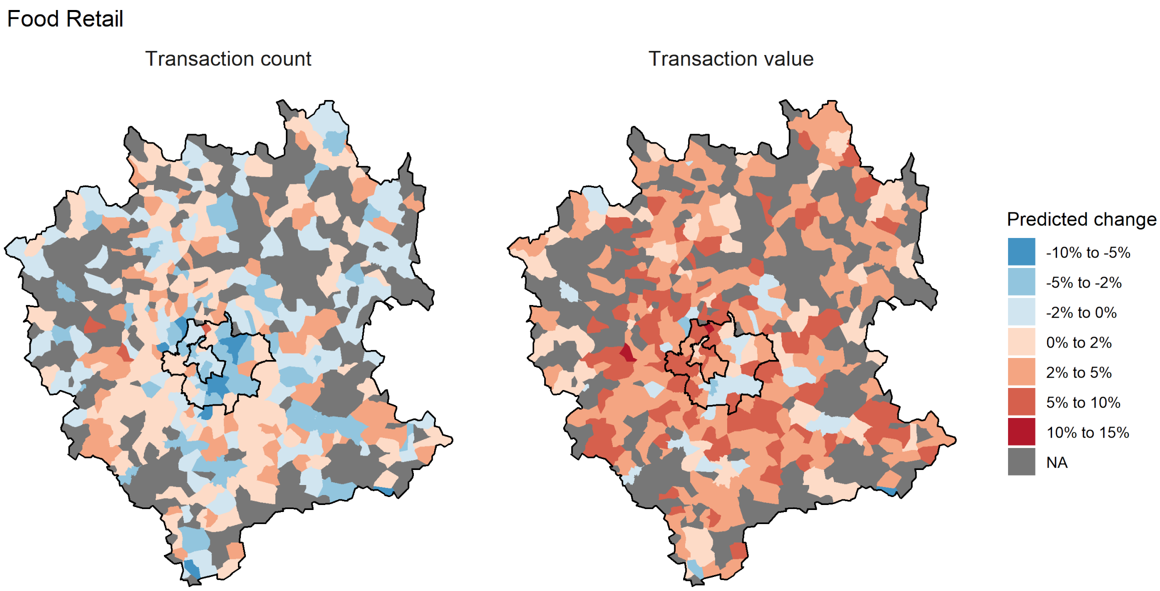
To quantify the overall economic impact of telework on each sector, we conduct counterfactual analyses that compare actual consumption patterns with those predicted under a zero-telework scenario. Figures 23 through 26 present the estimated effects of telework on transaction counts and values for four key sectors: Restaurants, Food Retail, General Retail, and Bars and Drinks. The Restaurants sector (Figure 23) shows a clear pattern where telework leads to a net reduction in both transaction counts and values. This negative effect reflects the dominant impact of reduced workplace presence, which outweighs the positive residential effects in this sector. The Food Retail sector (Figure 24) presents a more balanced picture, with the negative workplace effects nearly offset by positive residential effects, resulting in a smaller net impact.

General Retail (Figure 25) shows a pattern similar to Restaurants, with a net negative effect of telework. However, the magnitude of the effect is smaller, suggesting that general retail consumption is somewhat less sensitive to telework patterns than restaurant spending. The Bars and Drinks sector (Figure 26) exhibits the most positive net response to telework, with both transaction counts and values showing increases. This reflects the particularly strong positive residential effects in this sector, which outweigh the negative workplace impacts.



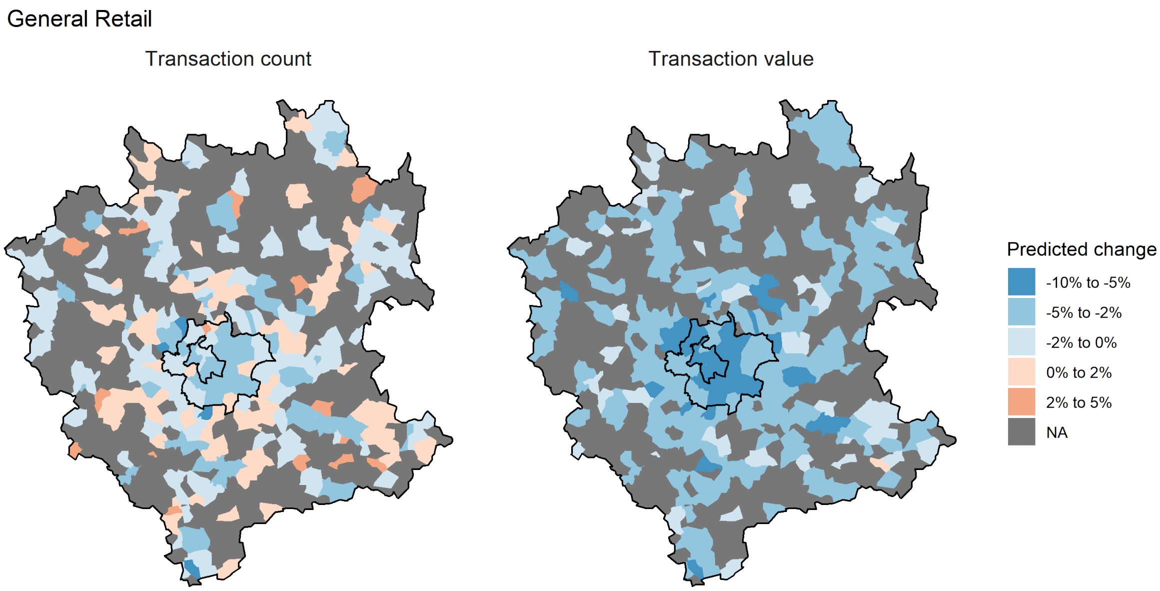
Note: The two figures show the effect of telework on transaction counts and transaction values, respectively, in the sector $s = \textit{Restaurants}$. This is computed as the weekly average of the ratio $(\tilde{y}_{ids} - \tilde{y}^0_{ids})/\tilde{y}^0_{ids}$, where $\tilde{y}_{ids}$ denotes the model-predicted values, $\hat{y}_{ids}$, averaged over day $d \in \{\text{Mon ; Tue ; Wed ; Thu ; Fri}\}$, and $\tilde{y}^0_{ids}$ denotes the counterfactual predicted values under a zero-telework scenario, $\hat{y}^0_{ids}$, also averaged over day d. Predictions are obtained from a model that includes municipality fixed effects, date-by-zone-type fixed effects, and the full set of control variables.

Figure 23: Effect of telework in Restaurants



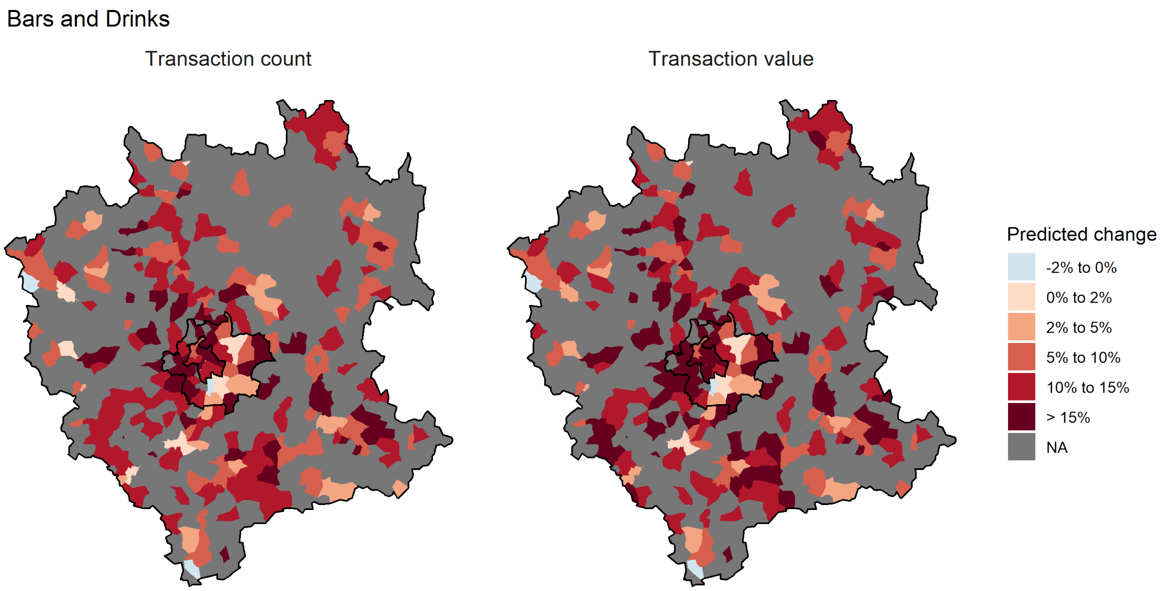
Note: The two figures show the effect of telework on transaction counts and transaction values, respectively, in the sector $s = \textit{Food Retail}$. This is computed as the weekly average of the ratio $(\tilde{y}_{ids} - \tilde{y}^0_{ids})/\tilde{y}^0_{ids}$, where $\tilde{y}_{ids}$ denotes the model-predicted values, $\hat{y}_{ids}$, averaged over day $d \in \{\text{Mon ; Tue ; Wed ; Thu ; Fri}\}$, and $\tilde{y}^0_{ids}$ denotes the counterfactual predicted values under a zero-telework scenario, $\hat{y}^0_{ids}$, also averaged over day d. Predictions are obtained from a model that includes municipality fixed effects, date-by-zone-type fixed effects, and the full set of control variables.

Figure 24: Effect of telework in Food Retail



Note: The two figures show the effect of telework on transaction counts and transaction values, respectively, in the sector $s =$ *General Retail*. This is computed as the weekly average of the ratio $(\tilde{y}_{ids} - \tilde{y}^0_{ids})/\tilde{y}^0_{ids}$, where $\tilde{y}_{ids}$ denotes the model-predicted values, $\hat{y}_{ids}$, averaged over day $d \in \{\text{Mon ; Tue ; Wed ; Thu ; Fri}\}$, and $\tilde{y}^0_{ids}$ denotes the counterfactual predicted values under a zero-telework scenario, $\hat{y}^0_{ids}$, also averaged over day d. Predictions are obtained from a model that includes municipality fixed effects, date-by-zone-type fixed effects, and the full set of control variables.

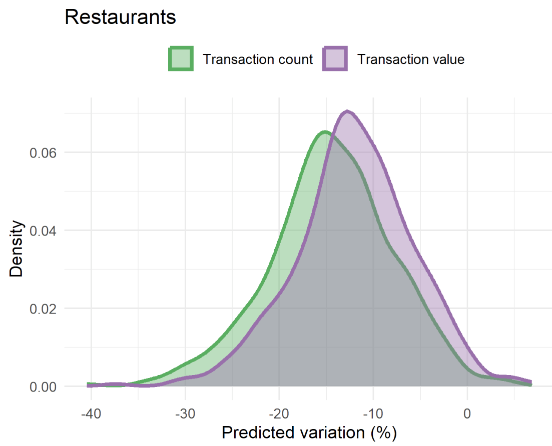
Figure 25: Effect of telework in General Retail



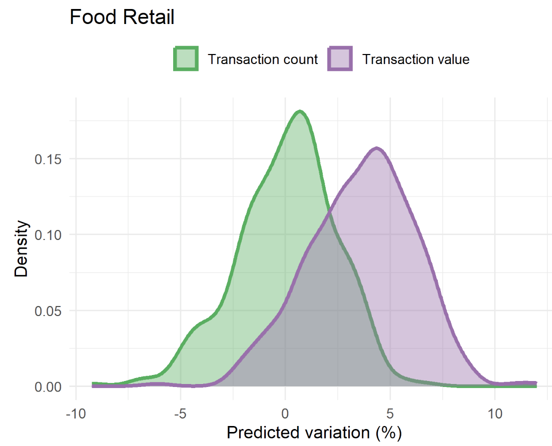
Note: The two figures show the effect of telework on transaction counts and transaction values, respectively, in the sector $s =$ *Bars and Drinks*. This is computed as the weekly average of the ratio $(\tilde{y}_{ids} - \tilde{y}^0_{ids}) / \tilde{y}^0_{ids}$, where $\tilde{y}_{ids}$ denotes the model-predicted values, $\hat{y}_{ids}$, averaged over day $d \in \{\text{Mon ; Tue ; Wed ; Thu ; Fri}\}$, and $\tilde{y}^0_{ids}$ denotes the counterfactual predicted values under a zero-telework scenario, $\hat{y}^0_{ids}$, also averaged over day d. Predictions are obtained from a model that includes municipality fixed effects, date-by-zone-type fixed effects, and the full set of control variables.

Figure 26: Effect of telework in Bars and Drinks

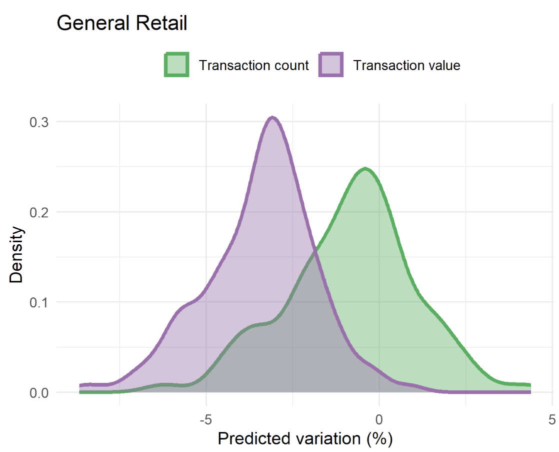
Figure 27 provides a comprehensive view of the distribution of predicted transaction changes across municipalities for each sector. The density plots reveal important patterns in the heterogeneity of sectoral responses. The Restaurants sector shows a concentration of municipalities experiencing negative effects, with relatively few municipalities showing positive responses to telework. In contrast, the Bars and Drinks sector displays a more balanced distribution, with a substantial proportion of municipalities experiencing positive effects. The Food Retail sector presents an interesting bimodal distribution, suggesting that municipalities are divided between those that benefit from telework (likely residential areas with increased local consumption) and those that experience declines (likely commercial areas with reduced workplace presence). General Retail shows a pattern similar to Restaurants, though with a slightly wider spread of effects across municipalities. These sectoral analyses provide critical insights into the heterogeneous economic impacts of telework adoption. The variation in responses across sectors highlights the importance of considering sector-specific dynamics when designing policies related to telework regulation or economic stimulus. The particularly strong effects in the Bars and Drinks sector suggest that policies promoting telework might have unintended positive consequences for local social establishments, while the negative impacts on Restaurants and General Retail indicate potential challenges for commercial districts that rely on workplace-related consumption.



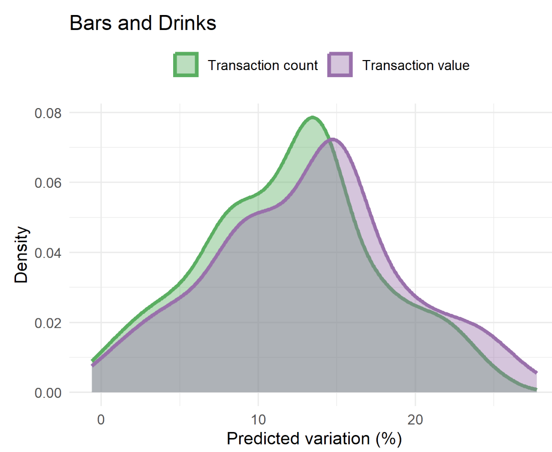
(a) Restaurants



(b) Food Retail



(c) General Retail



(d) Bars and Drinks

Note: The two lines display the density functions of the estimated effect of telework on transaction counts and transaction values, respectively. For each sector s, predicted effects are computed as the weekly average of the ratio $(\tilde{y}_{ids} - \tilde{y}^0_{ids})/\tilde{y}^0_{ids}$, where $\tilde{y}_{ids}$ denotes the model-predicted values, $\hat{y}_{ids}$, averaged over day $d \in \{\text{Mon; Tue; Wed; Thu; Fri}\}$, and $\tilde{y}^0_{ids}$ denotes the counterfactual predicted values under a zero-telework scenario, $\hat{y}^0_{ids}$, also averaged over d. Predictions are obtained from a model that includes municipality fixed effects, date-by-zone-type fixed effects, and the full set of control variables.

Figure 27: Density of municipalities' predicted transaction changes associated with telework, by sector

D Appendix to Section 5

This appendix extends our core analysis by examining the spatial dimensions of telework's economic impacts through two complementary approaches. First, we investigate spatial heterogeneity in marginal effects across different zone groups within the metropolitan area, revealing how telework impacts vary between urban cores, commuting zones, and rural areas. Second, we aggregate these spatial effects to quantify the overall economic impact of telework at the metropolitan scale. Together, these extensions provide a comprehensive spatial perspective on telework's economic impacts, moving beyond our core municipal-level analysis to examine both local heterogeneity and metropolitan-wide aggregate effects.

D.1 Spatial Spillover Model

Our spatial spillover model, presented in Table 23, incorporates both direct telework effects within municipalities and indirect effects from neighboring areas, allowing us to capture the complex spatial interdependencies in consumption patterns.

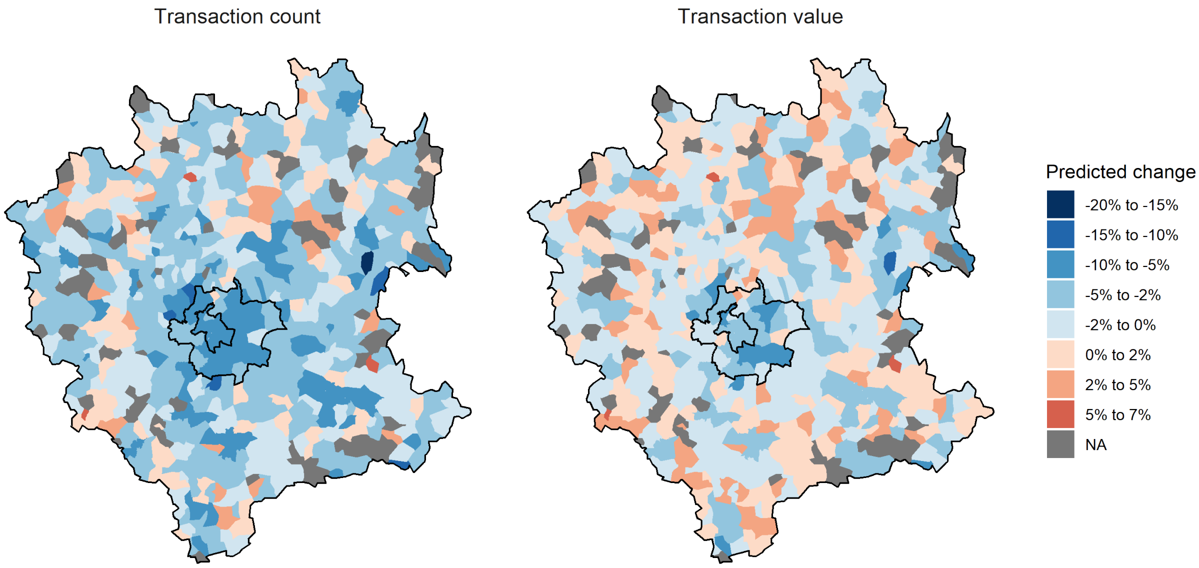
Figure 28 visualizes the average daily effects of telework on both transaction counts and values, incorporating spatial spillovers from neighboring municipalities. This aggregate analysis reveals that while telework generates net negative effects across most zone groups, the magnitude varies significantly, with Lyon city experiencing an 8.08% reduction in transactions and rural commuting zones showing a much smaller 2.05% decline.

Table 24 quantifies these net total effects by zone group, highlighting both the economic costs of reduced workplace presence and the partial offsetting benefits of increased residential consumption.

	Transaction count		Transaction value	
	(1)	(2)	(3)	(4)
$RT^{(\mathcal{H})} \times$ Lyon city	2.35***	2.01***	1.10**	0.876**
	(0.850)	(0.736)	(0.514)	(0.421)
$RT^{(\mathcal{H})} \times$ Rest of the core	1.14***	0.990**	1.24***	1.11***
	(0.431)	(0.414)	(0.419)	(0.387)
$RT^{(\mathcal{H})} \times$ Urban commuting zone	0.585	0.707	-0.248	0.079
	(0.483)	(0.492)	(0.550)	(0.560)
$RT^{(\mathcal{H})} \times$ Rural commuting zone	1.42	1.44	2.16**	2.24**
	(0.906)	(0.886)	(1.01)	(0.974)
$RT^{(\mathcal{W})} \times$ Lyon city	-4.06***	-3.49***	-3.26***	-2.69***
	(1.05)	(0.977)	(0.794)	(0.697)
$RT^{(\mathcal{W})} \times$ Rest of the core	-1.54**	-1.42**	-1.17	-1.03
	(0.629)	(0.614)	(0.758)	(0.727)
$RT^{(\mathcal{W})} \times$ Urban commuting zone	-1.16***	-1.06**	-1.47**	-1.44**
	(0.424)	(0.444)	(0.585)	(0.613)
$RT^{(\mathcal{W})} \times$ Rural commuting zone	-1.50**	-1.51**	-1.21	-1.42*
	(0.754)	(0.749)	(0.788)	(0.777)
$RT^{(\mathcal{H})}_{\text{neighbors}} \times$ Lyon city	2.23**	2.06**	2.44***	2.36***
	(0.980)	(0.879)	(0.534)	(0.424)
$RT^{(\mathcal{H})}_{\text{neighbors}} \times$ Rest of the core	0.911	0.769	1.82	1.48
	(1.08)	(1.01)	(1.38)	(1.24)
$RT^{(\mathcal{H})}_{\text{neighbors}} \times$ Urban commuting zone	0.375	0.044	1.27	0.899
	(0.768)	(0.724)	(0.835)	(0.759)
$RT^{(\mathcal{H})}_{\text{neighbors}} \times$ Rural commuting zone	1.09	0.948	-0.505	-0.576
	(1.50)	(1.44)	(1.67)	(1.60)
$RT^{(\mathcal{W})}_{\text{neighbors}} \times$ Lyon city	-4.93**	-4.35**	-5.01***	-4.67***
	(2.34)	(2.21)	(1.40)	(1.12)
$RT^{(\mathcal{W})}_{\text{neighbors}} \times$ Rest of the core	-1.47**	-1.63**	-2.12**	-2.22**
	(0.708)	(0.756)	(0.967)	(1.03)
$RT^{(\mathcal{W})}_{\text{neighbors}} \times$ Urban commuting zone	-0.259	-0.471	0.168	0.230
	(0.631)	(0.581)	(0.924)	(0.849)
$RT^{(\mathcal{W})}_{\text{neighbors}} \times$ Rural commuting zone	-1.73	-1.64	-0.912	-0.624
	(1.59)	(1.52)	(1.66)	(1.61)
$PT^{(\mathcal{H})}$		1.86*		0.786
		(0.962)		(0.976)
$PT^{(\mathcal{W})}$		1.28*		2.76***
		(0.776)		(0.775)
Rain		-0.008**		-0.006
		(0.004)		(0.005)
Public transp. disrupt.		0.005		0.004
		(0.007)		(0.009)
Fit statistics				
Observations	10,640	10,640	10,640	10,640
BIC	166,293.5	165,914.3	5,408,037.2	5,384,289.5

Note: Signif. codes: ***: 0.01, **: 0.05, *: 0.1. Clustered standard-errors at the municipality level in parentheses. All specifications include municipality and date-by-zone type fixed effects.

Table 23: Spatial spillovers, heterogeneity by zone group



Note: The two figures show the average daily effect of telework on transaction counts and transaction values, respectively. This is computed as the weekly average of the ratio $(\tilde{y}_{id} - \tilde{y}^0_{id})/\tilde{y}^0_{id}$, where $\tilde{y}_{id}$ denotes the model-predicted values, $\hat{y}_{id}$, averaged over day $d \in \{\text{Mon} ; \text{Tue} ; \text{Wed} ; \text{Thu} ; \text{Fri}\}$, and $\tilde{y}^0_{id}$ denotes the counterfactual predicted values under a zero-telework scenario, $\hat{y}^0_{id}$, also averaged over day d. Predictions are obtained from a model that includes average telework shares of contiguous municipalities, together with municipality fixed effects, date-by-zone-type fixed effects, and the full set of control variables.

Figure 28: Average daily effect of telework (spatial spillover model)

		Transaction count			Transaction value		
	N_g	$\sum_g y_{ig}$	Δ_g %	Δ_g	$\sum_g y_{ig}$	Δ_g %	Δ_g €
Lyon city	9	227,074	-8.08	-18,342	6,195,465	-2.38	-147,585
Rest of the core	30	190,564	-7.55	-14,386	6,944,555	-2.55	-177,377
Urban commuting zone	166	254,930	-4.53	-11,538	10,467,588	-0.88	-92,499
Rural commuting zone	327	58,652	-2.05	-1,205	2,331,438	0.87	20,193
All	532	731,220	-6.22	-45,471	25,939,046	-1.53	-397,269

Note: Column 1 reports the number of municipalities in each group. Column 2 gives the total daily number of transactions within each group, calculated as the sum of weekly municipality averages. Column 3 presents the estimated aggregate percentage change in transaction counts attributable to telework, and Column 4 shows the corresponding change in transaction counts. Column 5 reports the total value of transactions within each group, also calculated as the sum of weekly municipality averages. Column 6 presents the estimated aggregate percentage change in transaction values attributable to telework, and Column 7 shows the corresponding change in transaction values.

Table 24: Aggregate Impact of Telework: Predicted Percentage Change in Transactions by Spatial Zone

E Appendix: Alternative Measures of Telework

E.1 Model

We use anonymized mobile phone data to track individuals' presence in their residential area during working hours on weekdays. This information allows us to infer realized teleworking behavior for each municipality and day of the week.

We develop a method to estimate the daily realized telework rate at the municipal level, accounting for the daily share of part-time workers on day-off who may remain within their residential area. These individuals have similar preferences to teleworkers for staying at home on certain weekdays, thereby potentially confounding telework estimates.

To estimate daily telework rates for a typical week at the municipal level, we model the number of residents present during working hours, captured through mobile phone data, as the sum of three distinct population groups:

$$\text{Residents}_{it} = \widehat{\alpha}_i \times \text{Inactives}_i + \sum_k \gamma_{gkt} \times \text{Part-time workers}_{ik} + \widehat{\beta_{it}} \times \text{Teleworkers}_i \tag{13}$$

where:

- Residents_{it} is the average daily count of residents present in their nighttime zone i (Iris) on day t, measured over four weeks of September 2022 using anonymized mobile phone location data.

- Inactives_i and $\text{Part-time workers}_{ik}$ denote respectively the inactive population (unemployed, students, housewives/husbands, retirees, etc.) and part-time workers by occupation k residing in Iris zone i, derived from census data.

- γ_{gkt} represents the day- and occupation-specific presence rate of part-time workers living in location type g (urban core, inner suburbs, outer suburbs, and outside the functional urban area), estimated from labor force survey data.

- Teleworkers_i is the teleworker population in Iris zone i, computed using combined census and labor survey data.

- $\widehat{\alpha}_i$ and $\widehat{\beta}_{it}$ are the unknown parameters capturing the share of inactive residents and the daily telework rate of teleworkers working from home, respectively, to be estimated through the model.

This approach relies on two key assumptions: (1) the share of inactives present at home does not vary daily, and (2) teleworkers work remotely on average 2.4 days per week, based on labor force survey data.

Using these constraints, we solve for $\widehat{\alpha}_i$ and $\widehat{\beta_{it}}$ to isolate the telework effect. This allows us to compute realized telework shares at home ($\text{RT}_{it}^{(\mathcal{H})}$) and workplace ($\text{RT}^{(\mathcal{W})}$) levels by combining $\widehat{\beta_{it}}$ with location-and-occupation-based telework potentials, τ_{kg}, and population census data.

E.2 Estimates for α_i and β_{it}

Raw estimates. Figure 29 shows the distribution of the computed share of inactive people, $\widehat{\alpha}_i$, supposed to be in their residence zone every day in a typical week. We allow $\widehat{\alpha}_i$ to be greater than 1 to consider intra-nighttime-zone commuters as well (we cannot observe them).

Figure 30 shows the distribution of the computed shares of teleworkers working from home each day of a typical week, $\widehat{\beta_{it}}$. Some values are below zero and greater than one. This is a problem for interpretability.

$\widehat{\beta_{it}}$ correction. We suggest two correction methods for $\widehat{\beta_{it}}$: (1) a min-max normalization of the coefficients for each zone, under the constraint that the sum is equal to 2.4; (2) a min-max normalization and sum-correction of the coefficients only for those zones with at least one computed share out of the bound [0;1]. Both methods rely on those two steps (with the exception that the second method apply those rules on selected observations):

1. Min-max normalization

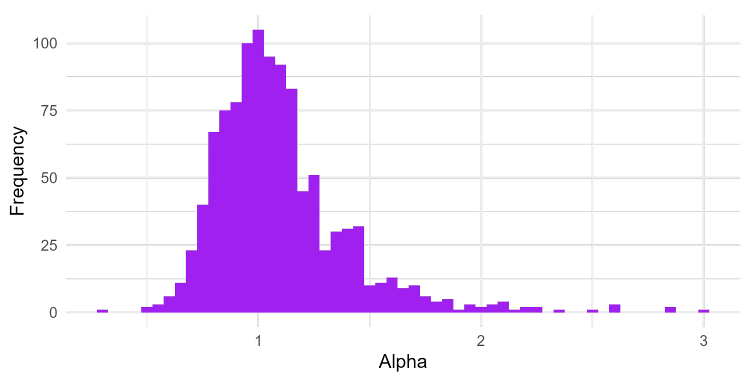
$$\beta_{it}^{norm} = \frac{\beta_{it} - \min_d \beta_{id}}{\max_d \beta_{id} - \min_d \beta_{id}} \tag{14}$$

2. Sum correction

$$\delta_i = 2.428 - \sum_{t=1}^{n_i} \beta_{it}^{norm} \tag{15}$$

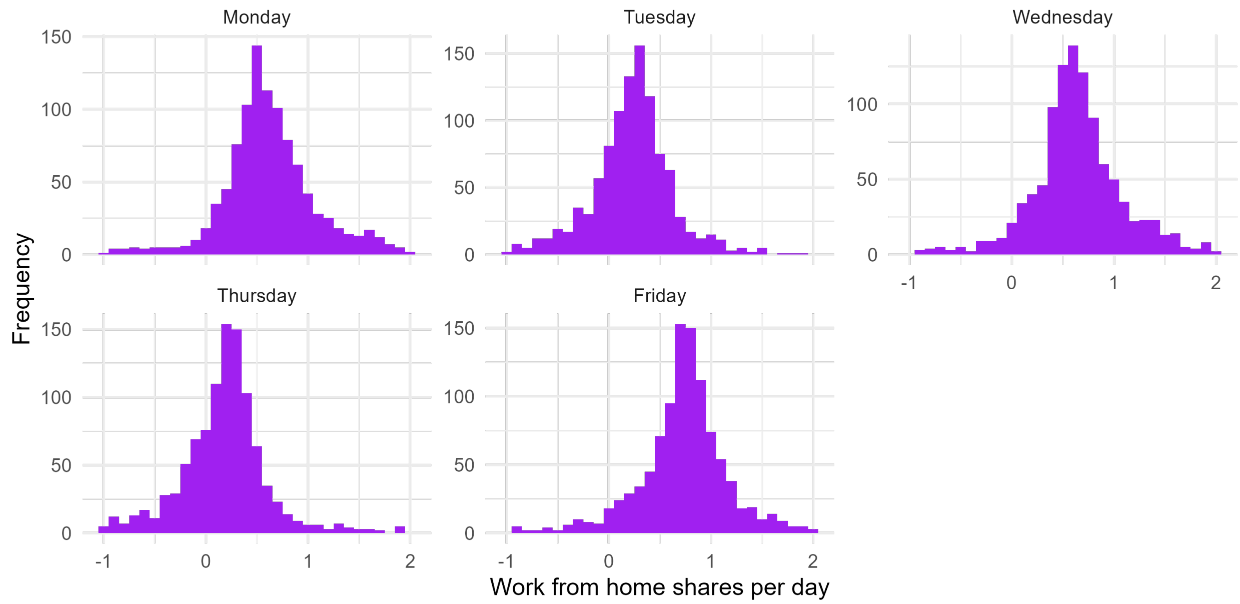
$$\beta_i^{scaled} = \begin{cases} \beta_i^{norm} + \frac{\delta_i}{n_i - 2} & \text{if } \beta_i^{norm} \in (0;1) \\ \beta_i^{norm} & \text{otherwise} \end{cases} \tag{16}$$

The two methods ensures that shares are within [0;1] and allow to preserve the relative ranking of the coefficients across days. The first method gives coefficients systematically relative to the minimum and the maximum practice over a week for each zone. The second method better preserves the distribution of the original coefficients. The pitfall of both methods is that they will introduce non-classical measurement error bias in our main model, which aims at explaining local consumption.



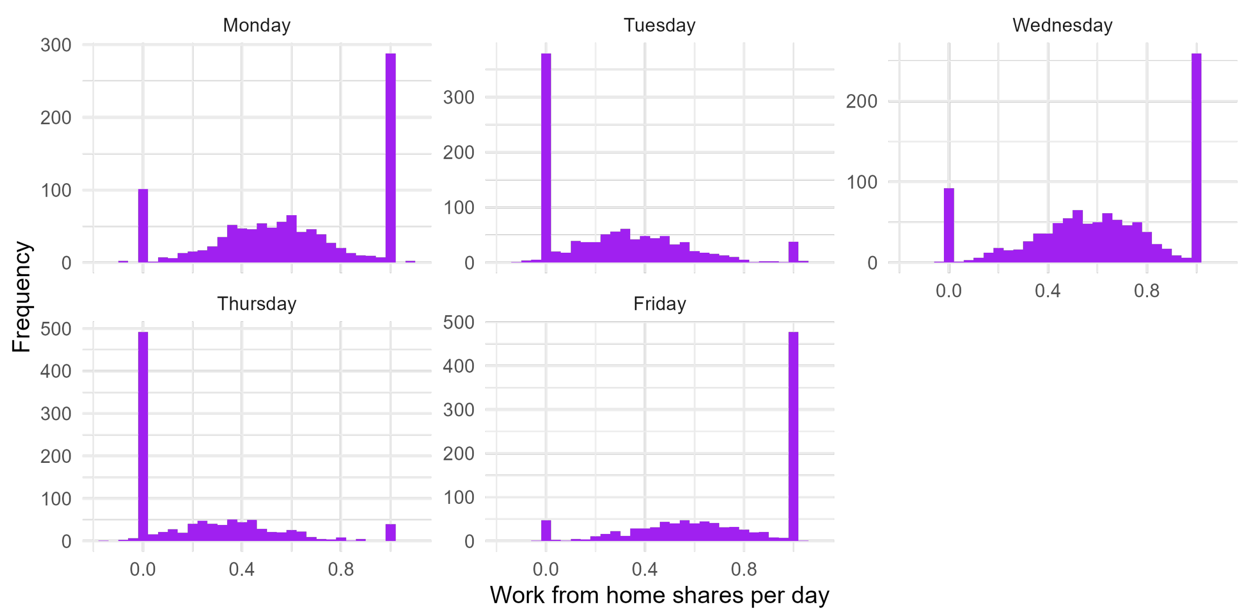
Note: The figure shows the distribution of the computed share of inactive residents supposed to be in their residence zone during working hours on weekdays.

Figure 29: Alpha



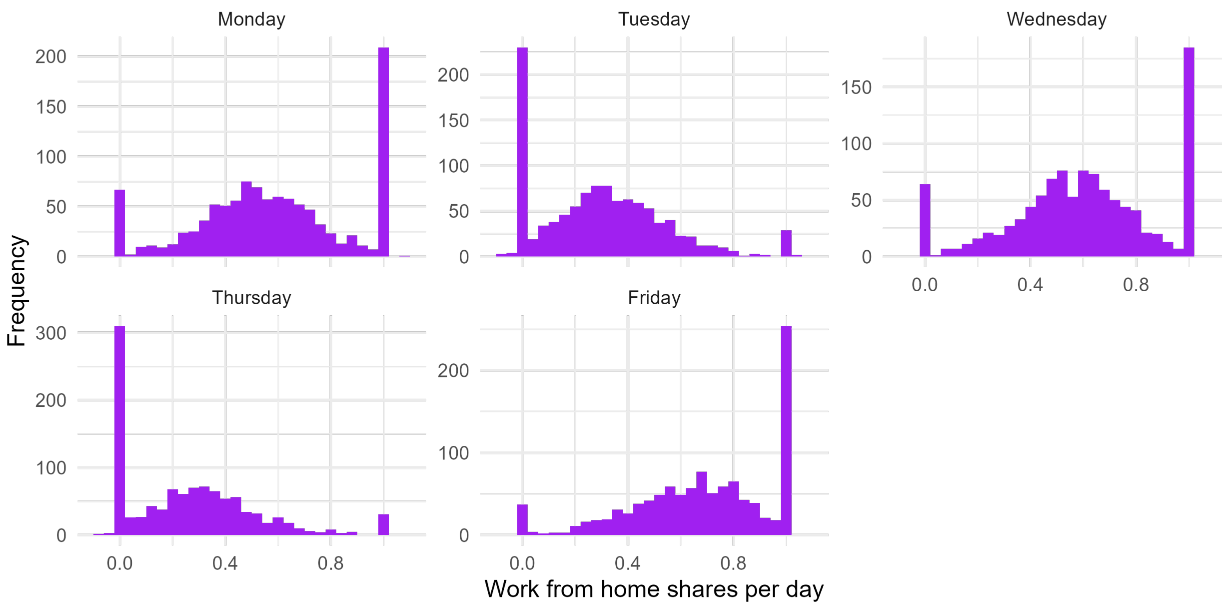
Note: The figure shows the distribution of the computed share of resident teleworkers supposed to be in their residence zone (working from home) during working hours on each weekday.

Figure 30: Raw Beta



Note: The figure shows the distribution of the normalized and rescaled share of resident teleworkers expected to be in their residential zone (working from home) during working hours for each weekday.

Figure 31: Scaled Beta[(1)]



Note: The figure shows the distribution of the computed share of resident teleworkers expected to be in their residential zone (working from home) during working hours for each weekday. When at least one observation for an Iris zone falls outside the [0,1] range, all weekday observations for that Iris zone are normalized and rescaled.

Figure 32: Scaled Beta$^{(2)}$ (on selected observations - those with Beta out of the bound [0;1])