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

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Abstract

While previous studies examine the impact of telework on consumption either near residences or workplaces, the net effect on local demand remains unclear. Using high-frequency mobile phone and card transaction data from Lyon, France's second-largest metropolitan area, we identify two causal demand shocks: a 1pp increase in work-from-home presence raises local spending by 1%, and a 1pp decrease in workplace presence reduces spending by 1.3%. Aggregating these opposing effects, we find a small and statistically insignificant decline in weekday offline consumption, suggesting that most spending shifts from workplace to home. We find that working from home is associated with a moderate spatial shift of spending from urban cores to residential suburbs, and a slight sectoral reallocation from restaurants toward food retail and bars.

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

JEL Codes: R11, R12, J22, L81

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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 net impact on local consumption, remain debated. 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, 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.

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

[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 12 for annual telework statistics.

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 firms' and workers' scheduling decisions and is therefore plausibly exogenous to short-term shocks in 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 four findings with significant implications for 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.

Second, while the average spending substitution from workplace to home is 0.72—meaning that a 1-percentage-point increase in home presence offsets 72% of the losses from a 1-percentage-point increase in workplace absence—this estimate is not statistically different from unity. This provides the first direct evidence that spending is nearly fully reallocated from workplace to home, leaving aggregate consumption unchanged. In contrast, for consumer visits to merchant establishments, as proxied by transaction counts, the substitution rate is only 0.57 (significantly below unity), indicating partial substitution and reflecting differences in consumption behavior between home and the workplace.

Third, telework reduces weekday transaction counts, with the largest declines in central urban areas: -6.8% in Lyon city, -6.7% in the rest of the urban core, -4.8% in the urban commuting zone, and -2.7% in rural municipalities. However, transaction values remain statistically unchanged across all zones, indicating that telework redistributes, rather than reduces, offline spending, shifting consumption from the urban core to the commuting zone. Our analysis shows that 5% of municipalities in the Lyon metropolitan area experience a significant decline in sales compared to a zero-telework scenario. Losses are largest in urban and central municipalities, highlighting the vulnerability of high-density areas to telework-induced demand shocks. In contrast, 9% of all municipalities, primarily residential municipalities in the commuting zone, see significant increases in spending, illustrating how telework reshapes the region's economic geography.

Fourth, 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% (statistically significant), 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 may benefit from telework, emerging as local substitutes for socializing and remote work, with sales increasing by 16%, although not statistically significant. Similarly, food retail experiences gains in transaction value (+3%), driven by larger basket sizes as the number of shopping trips declines slightly (-2%), again not statistically significant. Although these latter sectors do not show significant aggregate effects, some municipalities do, and local average demand effects are significantly different from zero. Together, our results 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. Critically, these heterogeneous effects also provide evidence of a causal relationship. Telework significantly impacts routine-based sectors, even those with transaction patterns misaligned with typical work-from-home days (e.g., restaurants, bars and cafés), while showing no effect in some other sectors where daily rhythms naturally align with telework schedules (e.g., general retail). This asymmetry rules out spurious correlations driven by reverse causality, such as consumption preferences influencing telework choices, and confirms that our estimates capture the true effect of telework on local demand.

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 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.

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. (2026) and Althoff et al. (2022), both of which have significantly contributed to our understanding of the spatial economic consequences of telework. Alipour et al. (2026), using a difference-in-differences design on German card transaction and mobile phone data (2019–2023), show that telework shifts spending from central business districts to residential areas. They estimate a spending elasticity of -3.7% with respect to WFH-induced declines in morning commuting: the greater the telework potential at the place of residence, the larger the mobility reduction and the higher the local spending post-covid. Conversely, they show that postcodes with high job density, without accounting for workers' telework potential at their workplace, saw spending fall by 0.05% for each one-percent increase in 2019 job density. However, by focusing primarily on spatial redistribution, their analysis leaves open the question of net aggregate effects of simultaneous increases in home presence and decreases in workplace attendance. Similarly, Althoff et al. (2022) focuses on the U.S. context, emphasizing declines in business district spending using cross-sectional variation in telework potential in a difference-in-differences setting, similar to Alipour et al. (2026), 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, at the daily and municipality level. Together, these contributions estimate the net effect of telework at both the municipality and aggregate levels, providing a more complete picture of its impact on urban economic activity and addressing questions left open by prior studies.

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, offering a more comprehensive approach to addressing endogeneity concerns than previously explored in Alipour et al. (2026) and Althoff et al. (2022). Using this approach, we provide a new empirical evidence that substitution between home- and workplace-based consumption is incomplete.

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. (2026) in Germany. Alipour et al. (2026) 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 4a, 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[4] 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,[5] 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. [6]

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

[4] 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.

[5] 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.

[6] 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.

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 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,[7] 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[8] 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 5 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.

[7]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.

[8]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).

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, $\tau_{g(i)k}$, in each occupation k residing in location type $g(i)$ (urban core, inner suburbs, outer suburbs, and outside FUA). The resulting values are reported in Table 12 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:

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

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

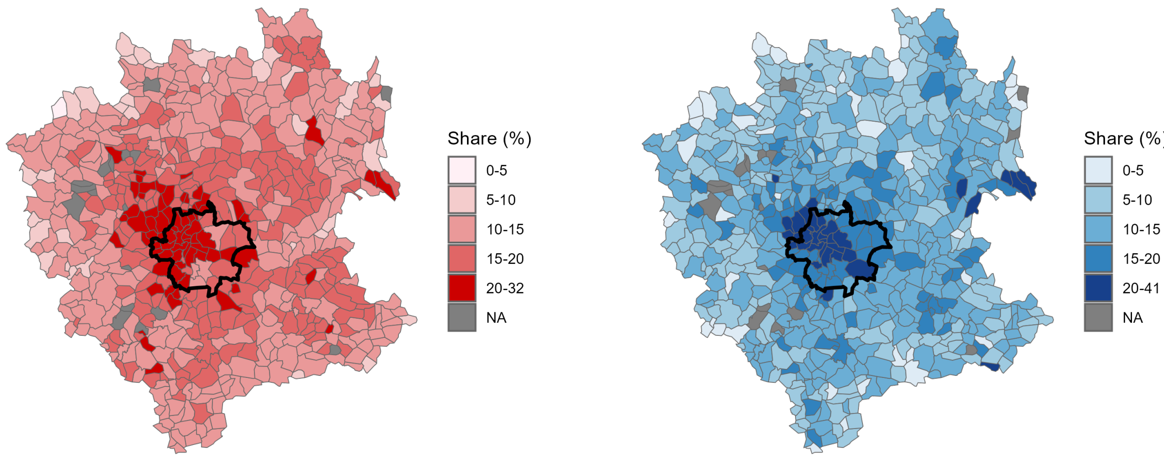
where $\mathrm{Workers}_{ijk}$ denotes workers in occupation k, living in municipality i and employed in j; $\mathrm{Workers}_i^{(\mathcal{H})} = \sum_{jk} \mathrm{Workers}_{ijk}$ denotes the total amount of workers living in i ($\mathcal{H}$ for home); $\mathrm{Workers}_j^{(\mathcal{W})} = \sum_{ik} \mathrm{Workers}_{ijk}$ 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

Using this approach, we estimate that roughly 220,000 people work from home in the Lyon area—about 19% of the working population—with 60% living in the urban core and 70% 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



(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, $\mathrm{TE}_i^{(\mathcal{H})}$ and $\mathrm{TE}_j^{(\mathcal{W})}$

home for reasons unrelated to telework but whose presence patterns could otherwise confound telework estimates. The model is written as follows:

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

where Residents_{it} is the average daily count of residents[9] 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 $\text{Part-time workers}_{ik}$ 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 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[10] of inactive residents at home

[9] 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.

[10] Coefficient $\widehat{\alpha}$ captures the effective daily presence rate of inactive residents at home, scaled to reflect observed counts in the data. While theoretically interpretable as a share (bounded by 1), the OLS estimates in Table 1 yield values slightly above 1 due to two factors: (1) the model's unconstrained estimation, which allows $\widehat{\alpha}$ to absorb scaling effects in the count data (Residents_{it}, Inactives_i), and (2) the omission of same-Iris workers in the census-based inactive classification. Since workplace information is only available at the municipality level, residents working within their

(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 daily telework patterns.[11]

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

Dependent Variable:	Residents in their nighttime zone net of part-time workers on day off		
Model:	(1) All FUA	(2) Urban core	(3) 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.

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

Iris of residence (e.g., local businesses, remote workers) are not classified as inactive but contribute to the observed presence rate, leading to an upward bias in $\widehat{\alpha}$.

[11] Table 13 in Appendix B.3 presents robustness checks including date fixed effects, reinforcing confidence that the estimates capture labor-related telework patterns rather than broader patterns in residential presence. Validation against on-site attendance data from a Paris-based public institution (October 2022–February 2024; see Appendix B.4) shows close alignment with our estimates. Together, these checks confirm the reliability of our results.

core municipalities are estimated to work remotely 3.4 days per week on average, compared to 2.5 days in the commuting zone.[12]

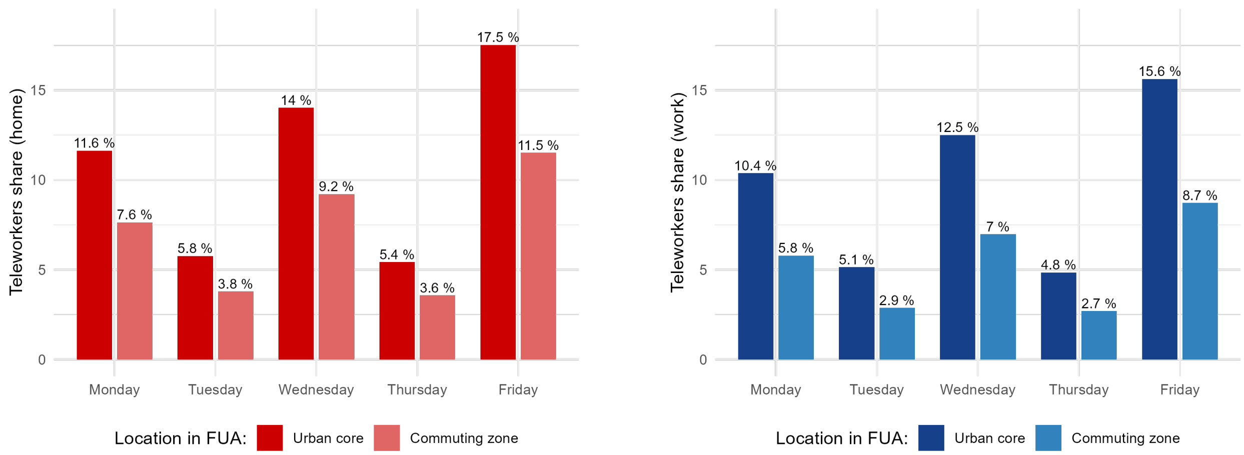
Using the estimated $\widehat{\beta}$, we can compute daily telework shares – the daily shares of all employed workers working from home – for each municipality and day both from the residence perspective, $\text{WFH}_{it}^{(\mathcal{H})} = \widehat{\beta}_t \text{TE}_i^{(\mathcal{H})}$, and workplace perspective, $\text{WFH}_{jt}^{(\mathcal{W})} = \widehat{\beta}_t \text{TE}_j^{(\mathcal{W})}$. 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 from home – $\text{WFH}_{it}^{(\mathcal{H})}$ and $\text{WFH}_{it}^{(\mathcal{W})}$ 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.

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. We do so 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.

[12] The discrepancy between the pooled estimate (2.417 days/week in column 1) and the sums of the subgroup estimates (3.387 and 2.518 days/week in columns 2–3) arises because the pooled model imposes a common schedule of $\widehat{\beta}$ across all municipalities, while the subgroup models estimate zone-specific schedules. The pooled coefficients are therefore not a simple weighted average of the subgroup coefficients, as they reflect a constrained optimization where the same daily telework intensities are applied uniformly across the entire sample. This explains why the subgroup sums exceed the pooled estimate: the urban core and commuting zone exhibit distinct telework rhythms (e.g., higher intensity on Fridays in the core), which are averaged out in the pooled model. Moreover, the external benchmark of 2.428 days/week is a regional average (Auvergne–Rhône–Alpes), not specific to the Lyon FUA. The higher intensities observed in the urban core (3.387 days) and commuting zone (2.518 days) are consistent with this regional average, as they reflect local variations in telework practices (e.g., higher teleworkability in dense employment hubs). Finally, while the raw sums of the subgroup coefficients (3.387 and 2.518) appear to exceed the pooled estimate, it is important to note that statistically insignificant coefficients (e.g., Tuesday and Thursday in the commuting zone, column 3) should not be interpreted as effective telework days. When accounting for statistical significance (e.g., setting insignificant $\widehat{\beta}_t$ to zero), the implied average converges to approximately 2.4 days/week, aligning with both the pooled estimate and the regional benchmark.



(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 $\text{WFH}_{it}^{(\mathcal{H})} = \widehat{\beta}_t \text{TE}_i^{(\mathcal{H})}$, where $\text{TE}_i^{(\mathcal{H})}$ 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 $\text{WFH}_{jt}^{(\mathcal{W})} = \widehat{\beta}_t \text{TE}_j^{(\mathcal{W})}$, where $\text{TE}_j^{(\mathcal{W})}$ is defined in Equation 2.

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

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:

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

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 $\text{WFH}_{it}^{(\mathcal{H})}$, which denotes the estimated share of employed residents working from home in municipality i on date t, and $\text{WFH}_{it}^{(\mathcal{W})}$, 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.[13] Municipalities' 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.[14]

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 sub-

[13] These fixed effects are crucial for identification, as spending follows systematic weekly cycles, with peaks on Wednesdays and Fridays (Figure 5). Including date × urbanization-group fixed effects removes this source of confounding with telework patterns, ensuring that telework effects are identified from variation orthogonal to these cycles.

[14] We address potential spatial correlations across neighboring municipalities and temporal dependencies across weekdays by implementing a two-way clustering of standard errors by municipality and date. As demonstrated in Appendix C.2 (Table 17), two-way clustering yields only modest increases in standard errors (e.g., from 0.213 to 0.388 for θ_1 in our preferred specification) while preserving the statistical significance of all key coefficients, including the work-to-home substitution rate. This confirms that our findings are robust to unmodeled spatial and temporal dependencies.

stitution rate as the ratio of the estimated marginal effects: $|\theta_1/\theta_2|$.[15]

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. This ratio captures the relative strength of the transaction response to a telework-induced one percentage point increase in residents present at home versus a one percentage point increase in workers absent from the workplace. Weighting $|\theta_1/\theta_2|$ by the ratio of the average number of workers working per municipality to the average number of workers living per municipality yields a measure of the relative strength of the transaction response generated by one additional teleworker being present at home versus one additional teleworker being absent from their workplace. Since the average numbers of resident workers and workplace workers are similar, $|\theta_1/\theta_2|$ can be directly interpreted as the substitution rate between home consumption and workplace consumption induced by a one-unit change in teleworker presence at the municipality level.[16]

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.

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 (variation) of telework is given by:

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

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.

[15] Using Equation 4, the marginal effects of residential telepresence and workplace teleabsence on local consumption are $\partial Y/\partial \mathrm{WFH}^{(\mathcal{H})} = \theta_1 Y$ and $\partial Y/\partial \mathrm{WFH}^{(\mathcal{W})} = \theta_2 Y$. 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.

[16] The exact formula for the average substitution rate at the municipality level, defined as the effect of one additional teleworker at home and one fewer at the workplace, is computed as follows: $\Big|[\exp(\theta_1/\overline{\mathrm{Workers}^{(\mathcal{H})}}) - 1]/[\exp(\theta_2/\overline{\mathrm{Workers}^{(\mathcal{W})}}) - 1]\Big|$ and approximately corresponds to $|\theta_1/\theta_2|$.

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. (2026) 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: $\Delta = \sum_i (\Delta_i\%/100) \times 1/T \sum_t y_{it}$, where y_{it} denotes the observed number or value of transactions in municipality i and date t. This 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.

Significance of the results. To evaluate the statistical significance of our estimates of the consumption substitution rate and aggregated telework effects, we derive their distributions and confidence intervals via a bootstrap procedure with 500 repetitions, as detailed in Appendix C.3.2.

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. 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.[17]

Result 2. Telework generates incomplete substitution in transaction frequency but statistically ambiguous effects on spending value. 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 0.575 for transaction counts and 0.721 for transaction values. These estimates indicate that the positive demand shock generated by teleworkers present at home offsets only part of the negative demand shock associated with teleworkers being absent from the workplace. The higher substitution rate for transaction values suggests that the monetary volume of spending is better preserved than the number of transactions, reflecting differences in the size and nature of purchases between home- and workplace-based consumption.

The substitution rate can be interpreted in two ways. First, it captures the share of transactions generated by a one–percentage-point increase in residents present at home due to telework relative to a one–percentage-point increase in workers absent from the workplace. Second, because the average denominators of our telework indicators are very similar in the Lyon Functional Urban Area, the substitution rate can also be interpreted as the share of transactions generated by a teleworker working from home relative to those generated by a teleworker working at the workplace. Consequently, the substitution rate interpreted as the ratio of changes in teleworker shares (57.5% in frequency and 72.1% in value) closely approximates the substitution rate interpreted as the ratio of changes in teleworker levels (60.3% in frequency and 75.6% in value).[18]

In levels, we find that a teleworker working from home contributes on average 21 euros to local spending, corresponding to approximately 0.61 additional transactions ($[\exp(\widehat{\theta_1}/\overline{\text{Workers}^{(\mathcal{H})}}) - 1] \times \overline{\text{Y}}$).[19] Conversely, the absence of a teleworker from the workplace reduces local spending by 28 euros, corresponding to approximately 1.01 fewer transactions. ($[\exp(\widehat{\theta_2}/\overline{\text{Workers}^{(\mathcal{W})}}) - 1] \times \overline{\text{Y}}$). The net effect is therefore a local decrease of 7 euros, corresponding to approximately 0.4 fewer transactions.

[17] Table 17 in Appendix C.2.1 shows that the estimated coefficients are still highly significant when clustering the standard errors at the municipality and date levels, accounting for potential correlation in the regression residuals both within municipalities over time and across municipalities on the same date.

[18] To interpret the substitution rate in terms of absolute changes in teleworkers, it is computed as: $|\theta_1/\theta_2| \times \overline{\text{Workers}^{(\mathcal{W})}}/\overline{\text{Workers}^{(\mathcal{H})}}$.

[19] Descriptive statistics for the variables of interest are reported in Table 8.

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Transaction count							
$\text{WFH}^{(\mathcal{H})}$	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)
$\text{WFH}^{(\mathcal{W})}$	-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)
$\text{PT}^{(\mathcal{H})}$		1.663*					1.665*
		(0.978)					(0.967)
$\text{PT}^{(\mathcal{W})}$		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)
$\text{WFH}^{(\mathcal{H})}$ × Public transp. disrupt.						0.720	
						(0.444)	
Public transp. disrupt. × $\text{WFH}^{(\mathcal{W})}$						-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							
$\text{WFH}^{(\mathcal{H})}$	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)
$\text{WFH}^{(\mathcal{W})}$	-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)
$\text{PT}^{(\mathcal{H})}$		0.838					0.849
		(0.968)					(0.964)
$\text{PT}^{(\mathcal{W})}$		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)
$\text{WFH}^{(\mathcal{H})}$ × Public transp. disrupt.						0.700**	
						(0.345)	
Public transp. disrupt. × $\text{WFH}^{(\mathcal{W})}$						-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, $|\theta_1/\theta_2|$, are computed using the Delta Method. In column 7, the bootstrap 90% CI for the substitution rate are [0.392; 0.904] for transaction count and [0.450; 1.263] for transaction value. Further details on the bootstrap procedure are provided in Appendix C.3.2. Table 27 additionally reports the substitution rates expressed in percentage points and in levels, together with their 90% CI.

To provide rigorous inference on the degree of consumption reallocation, standard errors are computed using the Delta Method (Pierce, 1982), which accounts for the nonlinearity of the substitution rates. For transaction frequency, the 90% confidence interval is [0.36; 0.79], indicating that the consumption substitution rate is significantly below unity. This reflects incomplete work-to-home consumption substitution, with a corresponding decrease in consumer visits due to telework. In contrast, for transaction values, the 90% confidence interval [0.40; 1.05] spans 1, revealing substantial heterogeneity across municipalities: in some cases, residential consumption fully or even over-compensate for workplace losses, while in others, the net effect remains negative. This variation highlights the importance of disaggregated analysis to capture the localized impacts of telework and reveal that telework may only impact spatial reallocation of spending rather than a net aggregated negative effect.

We further employ a bootstrap procedure (Appendix C.3.2) to estimate the distribution of the substitution rate both in terms of changes in the number of teleworkers—accounting for full variability across estimates and the weights of residential and workplace workers—and in percentage points, providing a more accurate measure of uncertainty than the Delta Method, which tends to underestimate it. Figure 25 presents the distribution of the consumption substitution rate in both percentage points and units, while Table 27 reports the average rates with 90% confidence intervals. For transaction frequency, the estimated substitution rates are 0.61 (percentage points) and 0.64 (units), with 90% confidence intervals of [0.39; 0.90] and [0.41; 0.93] respectively. As the entire interval lies below 1, this test still confirms incomplete consumption substitution. For transaction values, the estimates are 0.78 (percentage points) and 0.82 (units), with wider 90% confidence intervals [0.45; 1.26] and [0.46; 1.36], respectively. Since these intervals include 1, substitution cannot be concluded as statistically incomplete; the observed reallocation of spending may be consistent with near-full compensation in transaction value.

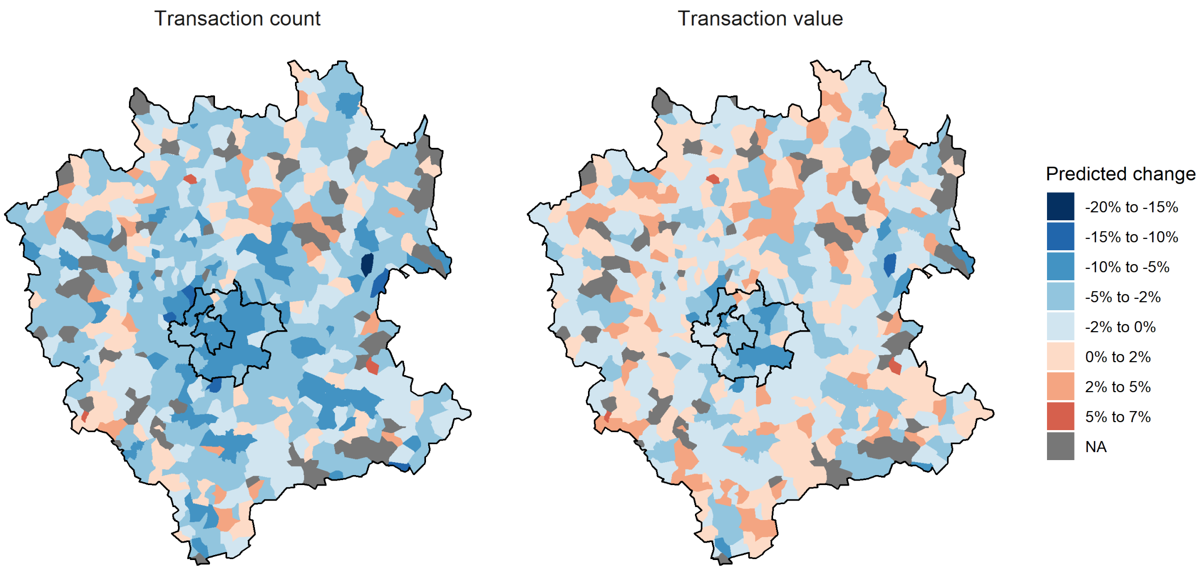
4.2.2 Net Effects of Telework on Local and Aggregate Consumption

We now analyze the net local and aggregate effects of telework on observed in-store consumption. 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 offline 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.[20]

[20] Figure 22 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 17-21 illustrate how these effects vary throughout the week, highlighting that telework's



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

We assess the significance of telework effects at the municipality level using a bootstrap procedure, presented in Appendix C.3.2. Figure 26 maps statistically significant (10% level) average effects on transaction frequency and value, Table 28 summarizes their distribution, and Table 29 reports their spatial distribution within municipality groups. For transaction frequency, only 168 of 532 municipalities exhibit a statistically significant telework effect: 26 positive (median 3.16%) and 142 negative (median -4.97%), showing a clear dominance of negative effects. The highest shares of significant effects are in Lyon city (44.4%) and the rest of the urban core (43.3%). Urban commuting zones show a slightly lower share (34.9%), while rural commuting zones have the lowest proportion (28.4%). Positive effects occur almost exclusively in rural areas. For transaction value, 70 municipalities show effects significantly different from zero: 46 positive (median 3.35%) and 24 negative (median -4.76%). Significant effects are mostly found in rural areas, while Lyon city shows none, and only a few municipalities in the urban core and urban commuting zones are affected. In the rural area, 13.1% municipalities experience a significant positive effect and 4% a negative effect. Overall, the results suggest that telework shifts spending away from urban cores toward less dense areas.

Result 4. Telework reduces transaction frequency but leaves overall aggregated spending nearly unchanged. Table 3 aggregates the effects across the four spatial areas of the Lyon FUA. Telework consistently reduces transaction counts across all zone groups, with the largest declines in central urban areas: Lyon city (-6.8%), the rest of the urban core (-6.7%), urban commuting zone (-4.8%), and rural commuting zone (-2.7%). Observed decreases in transaction values are smaller

impact on consumption is both spatially uneven and temporally dynamic, reflecting daily telework patterns.

(from -1% to –3.3%), but not statistically significant at the municipality level,[21] so overall spending remains largely preserved. Aggregated across the FUA, daily transaction counts decline by 5.8%, while total transaction value may be unchanged.

Overall, these results indicate that telework shifts consumer activity away from urban cores toward less dense areas. Transaction frequency declines most sharply in central urban areas, reflecting differences in consumption behavior between home and workplace: individuals purchase less frequently at home, where they can stock goods, while workplace constraints lead to more frequent on-site consumption. Crucially, total spending is preserved, suggesting near-complete substitution of spending from workplace to residence.

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

		Transaction count			Transaction value		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Zone group	N_g	$\sum_{i\in g} y_{ig}$	$\Delta_g\%$	Δ_g	$\sum_{i\in g} y_{ig}$	$\Delta_g\%$	Δ_g€
Lyon city	9	227,074	-6.82	-15,497	6,195,465	-2.98	-184,758
			[-12.03; -0.10]			[-8.62; 4.04]	
Rest of the core	30	190,564	-6.67	-12,713	6,944,555	-3.30	-229,428
			[-11.17; -0.64]			[-8.14; 2.28]	
Urban commuting zone	166	254,930	-4.82	-12,285	10,467,588	-2.39	-250,169
			[-8.02; -0.46]			[-6.05; 1.86]	
Rural commuting zone	327	58,652	-2.70	-1,584	2,331,438	-0.81	-18,803
			[-5.59; 0.78]			[-3.79; 2.77]	
All	532	731,220	-5.75	-42,079	25,939,046	-2.63	-683,158
			[-9.92; -0.38]			[-7.06; 2.63]	

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 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. In columns 3 and 6, bootstrap 90% confidence intervals are reported in square brackets. Further details on the bootstrap procedure are provided in Appendix C.3.2, and the corresponding results are presented in Table 26.

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: (1) *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 14.

[21]Results are not statistically significant as shown by the bootstrap 90% confidence intervals. Further details on the bootstrap procedure are provided in Appendix C.3.2, and the corresponding results are presented in Table 26.

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 significantly, while bars and food retail show non-significant increases. Routine-related sectors, such as Restaurants, Food Retail, and Bars and Drinks, exhibit the strongest and most significant average effects, both in transaction counts and values. The telework-induced local demand shocks are asymmetric: some sectors experience net reductions while others see net gains, as reflected by the estimated consumption substitution rates. However, only Restaurants exhibit a substitution rate significantly below one (both confirmed by the Delta Method and the bootstrap procedure),[22] whereas rates above one in other sectors are not statistically different from unity (and even include values below unit in the bootstrap confidence intervals).

Restaurants are the sector most adversely affected by telework-induced workplace absence. Our estimates reveal that a one percentage-point increase in the daily telework share at the workplace corresponds to a 4.2% decline in transaction counts and a 3.9% reduction in transaction value, while a one percentage-point increase in the daily telework share at the residence corresponds to a 1.1% increase in transaction counts and a 1.3% increase in transaction value. 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 (90% bootstrap CI: [8.4%; 44.1%] and [10.7%; 57.5%] for transaction count and value respectively). This stark imbalance underscores the sector's heavy reliance on workplace foot traffic, a demand driver that telework cannot replace. Unlike grocery shopping or leisure activities, which can be shifted to residential neighborhoods, restaurant visits may be 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), although these estimates are not statistically different from unity, as shown by the 90% bootstrap confidence intervals. This suggests a tendency toward increased at-home or local leisure consumption, but the evidence does not support a statistically significant over-compensation of workplace losses. Bars and cafés may serve as third places that substitute for both the home and the office on teleworking days, or as venues for socializing after a day spent working alone at home.

Food Retail also responds positively to telework, though more symmetrically. Following the values of the consumption substitution rate, transaction counts must decline slightly on weekdays and transaction values rise due to telework, although these effects are not statistically significant. As shown by the bootstrap 90% CI, [0.605; 1.560] for transaction counts and from [0.670; 5.237] for transaction values, both intervals include unity. The values of the average estimates are nonetheless consistent with larger grocery purchases for home-cooked meals and the time savings from reduced commuting, and aligns with intertemporal (weekend-to-weekday) substitution of consumption explored in Section 5.2.

[22] Further details on the bootstrap procedure are provided in Appendix C.3.2, and the corresponding results are presented in Table 32

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

	Restaurants (1)	Food (2)	Bars (3)	General (4)	Clothing (5)	Recreation (6)	Health (7)
Panel A: Transaction count							
$\text{WFH}^{(\mathcal{H})}$	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)
$\text{WFH}^{(\mathcal{W})}$	-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)
	[0.084; 0.441]	[0.605; 1.560]	[0.538; 7.188]	[0.173; 2.182]	-	-	-
Panel B: Transaction value							
$\text{WFH}^{(\mathcal{H})}$	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)
$\text{WFH}^{(\mathcal{W})}$	-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)
	[0.107; 0.575]	[0.670; 5.237]	[0.632; 10.862]	[0.046; 2.825]	-	-	-

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, $|\theta_1/\theta_2|$, are computed using the Delta Method. In columns 1 to 4, bootstrap 90% confidence intervals are reported in square brackets; they are not shown for the other columns, where the effect of telework is not statistically significant. Further details on the bootstrap procedure are provided in Appendix C.3.2, and the corresponding results are presented in Table 32.

Other sectors, such as General Retail, Clothing, Recreation, and Health services, show weaker or statistically insignificant responses, reflecting lower dependence on weekday routines and commuting patterns. 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.

This sectoral heterogeneity further reinforces a causal interpretation of the estimates. Telework effects are concentrated in activities closely tied to daily mobility and workplace presence, while sectors less exposed to these mechanisms remain largely unaffected. This pattern is unlikely to result from broad demand shocks or unobserved local trends, as such factors would be expected to affect multiple sectors similarly. Instead, the observed variation closely aligns with the behavioral channels induced by telework. Notably, telework has no significant effect on sectors whose daily consumption patterns mirror those of teleworkers (see Figure 6 in Appendix A.3) but significantly affects sectors with opposing consumption patterns. This differential impact provides further evidence that our estimates capture telework-induced changes in economic activity rather than spurious correlations.

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 municipality groups 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 transaction value: significant decline in restaurants, non-significant gains in bars and food retail. 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 (results are statistically significant, as shown by the bootstrap confidence intervals). Other sectors do not show telework effect statistically different from zero as shown by the bootstrap confidence intervals in Table 31. Nonetheless, the point estimates reveal informative patterns. 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. Taken together, these patterns indicate that telework not only redistributes consumption spatially but may also affect sectors differently depending on their reliance on workplace presence and their scope for at-home substitution, even when average effects are not precisely estimated.

Telework's sectoral impacts also reveal pronounced spatial heterogeneity, particularly within Lyon's urban core (see Figures 27-30 in Appendix C.4.1 for the estimated net effects on maps; see Figure 33 for the estimated net effects significantly different from zero). 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 (results are not statistically different from zero). 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 Figures 31 and 32): 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.

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

		Transaction count			Transaction value		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	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
			[-38.125; -17.348]			[-33.98; -12.894]	
Rest of the core	30	36,113	-25.93	-9,366	752,095	-22.06	-165,924
			[-35.040; -16.345]			[-30.952; -12.435]	
Urban commuting zone	144	35,712	-19.80	-7,072	912,920	-16.91	-154,396
			[-27.048; -12.438]			[-23.744; -9.424]	
Rural commuting zone	277	8,900	-13.68	-1,218	278,466	-10.76	-29,967
			[-20.289; -7.452]			[-16.88; -4.296]	
All	460	149,680	-24.64	-36,876	3,424,964	-20.64	-706,844
			[-33.999; -15.388]			[-29.168; -11.237]	
Food Retail							
Lyon city	9	86,739	-1.83	-1,587	1,719,538	4.19	71,994
			[-6.897; 6.570]			[-6.221; 18.720]	
Rest of the core	30	88,447	-2.30	-2,031	2,774,655	2.79	77,348
			[-6.718; 4.755]			[-5.876; 14.418]	
Urban commuting zone	139	122,539	-1.50	-1,835	4,561,443	2.18	99,543
			[-4.578; 3.676]			[-4.117; 10.765]	
Rural commuting zone	179	29,187	-0.03	-9	1,073,417	3.15	33,859
			[-2.634; 4.372]			[-2.304; 10.481]	
All	357	326,912	-1.67	-5,462	10,129,054	2.79	282,744
			[-5.652; 4.789]			[-4.836; 12.770]	
General Retail							
Lyon city	9	23,486	-2.09	-491	899,850	-6.19	-55,712
			[-11.799; 8.875]			[-16.442; 4.358]	
Rest of the core	30	23,424	-3.13	-732	1,370,675	-5.91	-81,037
			[-11.293; 5.568]			[-13.977; 2.814]	
Urban commuting zone	113	42,235	-2.12	-895	2,229,353	-4.38	-97,706
			[-8.315; 4.547]			[-10.486; 2.170]	
Rural commuting zone	113	6,738	-0.53	-35	294,973	-2.89	-8,536
			[-5.511; 5.062]			[-8.686; 2.523]	
All	265	95,884	-2.25	-2,154	4,794,850	-5.07	-242,990
			[-9.602; 5.918]			[-12.628; 2.845]	
Bars and Drinks							
Lyon city	9	13,824	17.56	2,427	250,043	19.43	48,571
			[-12.309; 60.055]			[-11.774; 63.770]	
Rest of the core	23	3,736	12.01	449	83,171	13.26	11,028
			[-12.731; 44.895]			[-11.227; 47.891]	
Urban commuting zone	93	5,310	8.81	468	130,821	10.14	13,260
			[-8.343; 30.612]			[-7.853; 32.723]	
Rural commuting zone	92	2,354	12.86	303	64,460	13.94	8,983
			[-2.944; 31.060]			[-2.149; 33.897]	
All	217	25,222	14.46	3,646	528,495	15.49	81,842
			[-10.033; 47.403]			[-9.192; 49.384]	

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. In columns 3 and 6, bootstrap 90% confidence intervals are reported in square brackets. Further details on the bootstrap procedure are provided in Appendix C.3.2, and the corresponding results are presented in Table 31.

Tables 33 and 34 further document the spatial heterogeneity in the sectoral impact of telework. Table 33 reports the distribution of the average net effect of telework across municipalities for the subset with statistically significant estimates. Table 34 reports the number of municipalities within each group that exhibit a statistically significant telework effect, disaggregated by positive and negative effects. In the *Restaurants* sector, 431 out of 460 (94%) municipalities with restaurant activity exhibit a statistically significant negative telework effect on transaction frequency, and 384 (83%) exhibit a statistically significant negative effect on transaction value. The effect is more negative in urban areas, consistent with reduced workplace-based consumption (see also the spatial distribution of the effects in Figure 33). In the *Food Retail* sector, most municipalities with a statistically significant telework effect (16%–24% of all municipalities) benefit from telework, with larger growth rates observed for transaction value. In the *Bars and Drinks* sector, all municipalities with a statistically significant telework effect (8%-18% of all municipalities) benefit from telework, with similar growth rates observed between transaction frequency and value. *Food Retail* and *Bars and Drinks* display more geographically diffuse effects, primarily within the commuting zone. In the *General Retail* sector, no significant telework effect is found.

Overall, these patterns suggest that telework induces a spatial reallocation of consumption, along with some sectoral substitution, away from employment centers toward residential areas, rather than an overall significant decline in local spending.

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 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 15) supports that our findings are not artifacts of measurement construction. To further ensure that our estimates of θ_1 and θ_2 are not driven by the mechanical relationship between home-presence ($\mathrm{WFH}^{(\mathcal{H})}$) and workplace-absence ($\mathrm{WFH}^{(\mathcal{W})}$), as both variables are constructed from the same residential daily telework patterns $\widehat{\beta}_t$, we restrict the analysis to municipalities with the largest divergences between home-presence and workplace-absence, which is exactly where independent variation can identify separate effects. As shown in Table 16, the estimated effects remain stable and significant across different quantiles selection, confirming that the model captures causal telework impacts rather than spurious correlations arising from mechanical mirroring. 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. First, we provide measurement error analysis using controlled simulations where we intentionally introduce varying levels of normally distributed noise into our telework variables. Figure 13 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 19), while another approach employs finer geographic resolution measures (method described in Section E, results in Table 20). 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 21–23 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 14 and 15 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 24). 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:

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

where $\sum_{j \neq i} w_{ij} \text{WFH}_{jt}^{(\cdot)}$ 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. Coefficients λ_1 and λ_2 are identified under the same exogeneity assumptions as θ_1 and θ_2.[23] 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

[23] 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.

in telework-induced presence at home in neighboring areas, $\text{WFH}^{(\mathcal{H})}_{\text{neighbors}}$, is associated with a 1.1% increase in both transaction counts and values. This pattern 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, $\text{WFH}^{(\mathcal{W})}_{\text{neighbors}}$, 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).

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

	Transaction count		Transaction value	
	(1)	(2)	(3)	(4)
$\text{WFH}^{(\mathcal{H})}$	1.006***	0.888***	0.865***	0.794***
	(0.264)	(0.244)	(0.259)	(0.270)
$\text{WFH}^{(\mathcal{W})}$	-1.616***	-1.525***	-1.311***	-1.271***
	(0.358)	(0.343)	(0.409)	(0.421)
$\text{WFH}^{(\mathcal{H})}_{\text{neighbors}}$	1.093**	1.021**	1.262***	1.145***
	(0.473)	(0.418)	(0.445)	(0.429)
$\text{WFH}^{(\mathcal{W})}_{\text{neighbors}}$	-1.132**	-1.312***	-1.077*	-1.056*
	(0.465)	(0.472)	(0.566)	(0.594)
$\text{PT}^{(\mathcal{H})}$		2.006**		1.032
		(0.966)		(0.991)
$\text{PT}^{(\mathcal{W})}$		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.

The coefficients associated with $\text{WFH}^{(\mathcal{H})}$ and $\text{WFH}^{(\mathcal{W})}$ 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.[24]

[24]Significant spatial heterogeneity in telework's spillover effects across the Lyon Functional Urban Area (FUA) is also existing (see Table 35 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

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[25] 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.

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

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

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 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.

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

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 $\mathrm{TE}^{(\mathcal{H})} \times$ 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

Table 7: Intertemporal consumption substitution induced by telework

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)	
$\text{TE}^{(\mathcal{H})}$ × 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)
$\text{TE}^{(\mathcal{H})}$ × Home			12.39***	14.65***
			(0.874)	(0.041)
Weekend × Home			-0.049	-0.146***
			(0.031)	(0.030)
$\text{TE}^{(\mathcal{H})}$ × Weekend × 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.

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 ($\text{TE}^{(\mathcal{H})}$ × Home), suggesting that individuals take advantage of their flexible schedules to shop locally during the 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 × Home), and this reduction intensifies with higher levels of telework ($\text{TE}^{(\mathcal{H})}$ × Weekend × 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 ($\text{TE}^{(\mathcal{H})}$ × 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 offline 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., 2026; Althoff et al., 2022). By ignoring one side of this phenomenon, previous studies likely underestimate the impact of telework-induced increased presence at home (Alipour et al., 2026) and decreased presence at the workplace (Althoff et al., 2022) 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 in terms of transaction frequency: home-based gains offset only about 57% of workplace losses. However, when measured in transaction values, substitution appears close to complete, as aggregate spending effects are not statistically different from zero. This suggests that telework primarily reduces purchase frequency—reflecting different consumption behaviors at home and in the workplace—and spatially redistributes spending rather than having an impact on the overall expenditure. Third, our study reveals a spatial redistribution of consumption from urban cores toward less dense areas. The 6.8% drop in transaction counts in Lyon city, compared with only 2.7% in rural municipalities, highlights the particular vulnerability of high-density employment hubs. Fourth, while point estimates suggest larger declines in transaction values in central urban areas (3.3%) than in rural commuting zones (0.8%), the bootstrap analysis indicates that these effects are not statistically different from zero, implying that overall spending remains largely stable despite shifts in where and how frequently purchases occur. Fifth, our sectoral analysis reveals heterogeneous impacts and potential sectoral substitution: restaurants experience sharp declines (-24% in Lyon city, -17% in urban municipalities in the commuting zone), while bars and food retail show positive responses to residential demand, though these effects are not statistically significant.[26] This heterogeneity suggests that targeted policies could help mitigate the localized adverse effects of telework while supporting sectors and areas that benefit from increased residential demand.

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 (Alipour et al. (2026) does so, but does not account for both dimensions of telework—presence at home

[26]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.

and absence from the workplace), or shifts in savings, investment, and broader consumption behavior. Finally, although we document a non-significant decline in total in-store spending, the extent to which telework impacts aggregate consumption overall remains uncertain since we do not consider cash and online payments. Additionnally, 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 more long-term discretionary purchases (e.g., electronics, home improvements) that our data on in-store transactions does not capture. 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.

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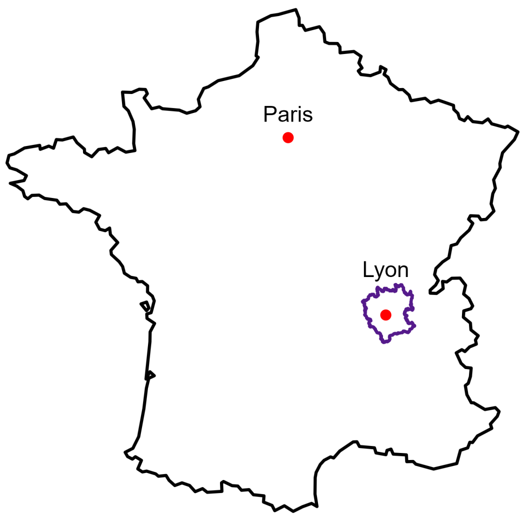
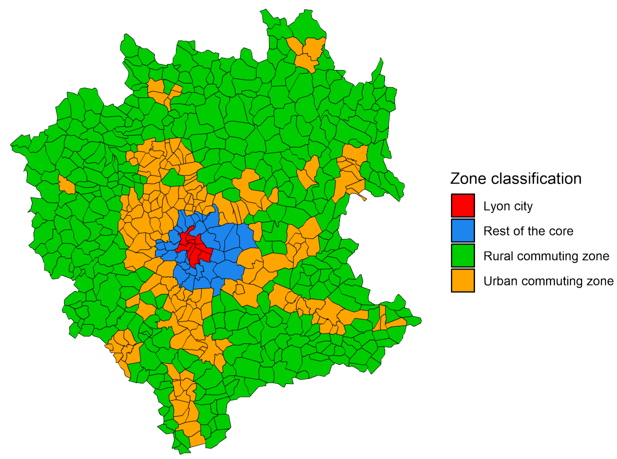
A Appendix to Section 2

A.1 Lyon FUA and municipalities classification

Figure 4a illustrates the geographic context of the study by displaying a map of France with the Lyon Functional Urban Area (FUA) highlighted. Figure 4b 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.



(a) Lyon Functional Urban Area (FUA) in France



(b) Classification of municipalities in the Lyon FUA

Figure 4: Maps of the Lyon Functional Urban Area and municipality classification.

Table 8: Summary statistics

	Min	1Q	Median	Mean	3Q	Max	Sd
Transaction frequency$_{it}$	0.00	13.00	105.00	1,335.58	598.00	59134.00	4509.73
Transaction value$_{it}$	0.00	579.75	3,694.50	47,403.92	21,397.50	2,260,169.00	147,079.61
$\text{Workers}_i^{(\mathcal{H})}$	34.76	435.78	815.61	2,161.45	1,679.50	70,498.43	5,435.30
$\text{Workers}_i^{(\mathcal{W})}$	4.35	154.70	359.02	2,265.48	1,219.16	94,432.88	7,357.69
$\text{Teleworkers}_i^{(\mathcal{H})}$	2.43	57.30	122.03	411.53	263.05	16,959.65	1,300.86
$\text{Teleworkers}_i^{(\mathcal{W})}$	0.25	12.83	39.59	424.05	167.87	22,911.13	1,697.57
$\text{Teleworkers}_{it}^{(\mathcal{H})}$	0.59	25.47	52.72	199.37	126.44	13,227.10	691.70
$\text{Teleworkers}_{it}^{(\mathcal{W})}$	0.06	5.30	17.38	205.44	75.97	17,868.75	900.01

Note: The table presents summary statistics for transaction frequency and value at the municipality–weekday level, the resident worker population ($\text{Workers}_i^{(\mathcal{H})}$) and workplace-based workers ($\text{Workers}_i^{(\mathcal{W})}$), as well as the estimated total and daily number of teleworkers at home and at the workplace.

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 9 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.

Table 9: Daily patterns of presence in the residence zone

	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 10 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.

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

	Residents share (1)	Residents share (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.

To make these results more interpretable, Table 11 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.

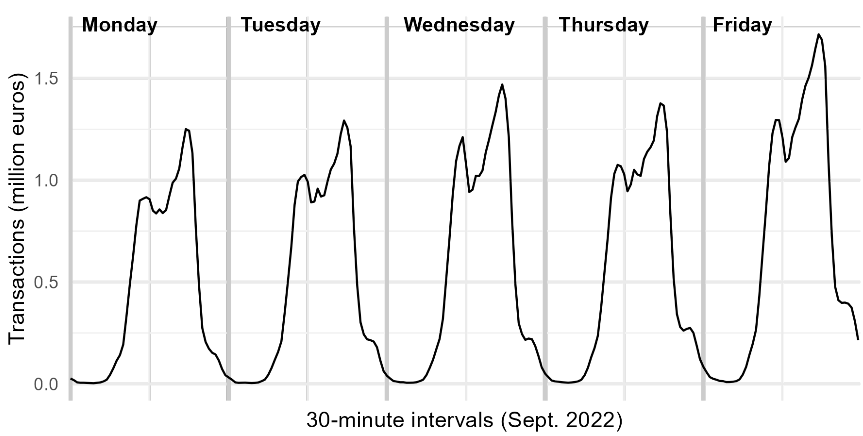
Table 11: Daily variation in resident presence by $TE^{(\mathcal{H})}$ levels

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 10.

A.3 Card daily transactions and spending in Lyon FUA

Figure 5 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 5: Typical weekday card spending

Figure 6 depicts sectoral daily deviations from the weekly mean number of transactions in the Lyon FUA (indexed to 100). The figure illustrates how transaction activity varies across weekdays, highlighting sector-specific patterns in consumer behavior. Overall, transactions in the Lyon FUA are not uniform throughout the week. Peaks occur on Wednesdays and Fridays for sectors such as Clothing and Beauty Retail, Food Retail, Health and Wellness, Sports and Recreation, and General Retail. In contrast, Bars and Cafés, as well as Restaurants, show a more gradual increase in activity over the weekdays.

Note: The figure shows average daily deviations from the weekly mean (indexed to 100) in the number of transactions by sector, based on observed transactions in the Lyon FUA during weekdays in September 2022.

Figure 6: Average daily deviations from weekly transaction frequency averages, by sector

B Appendix to Section 3

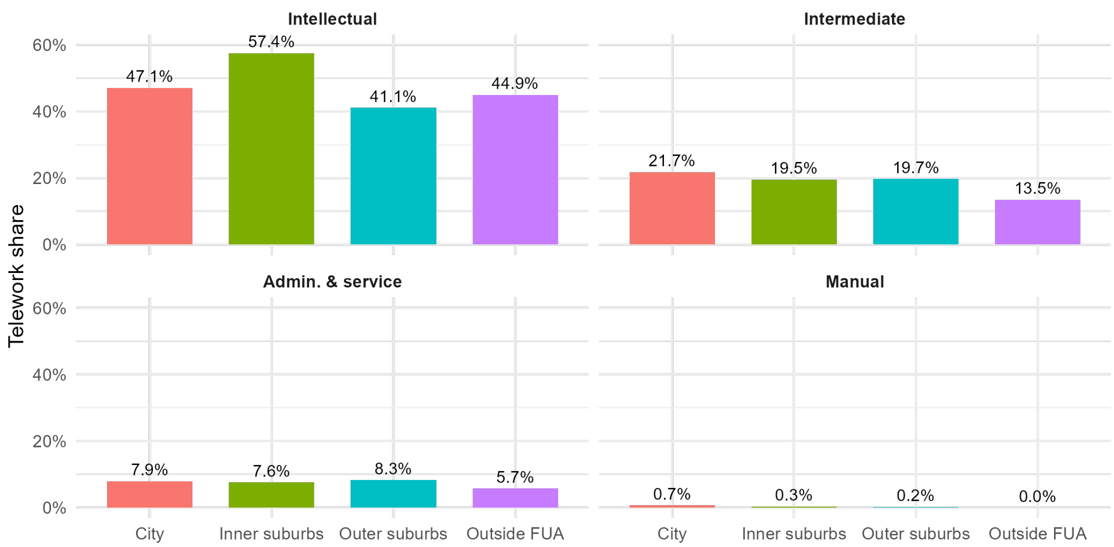
B.1 Telework statistics

Table 12 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.

Table 12: Telework practice by aggregated professional category in France from 2017 to 2024

	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.

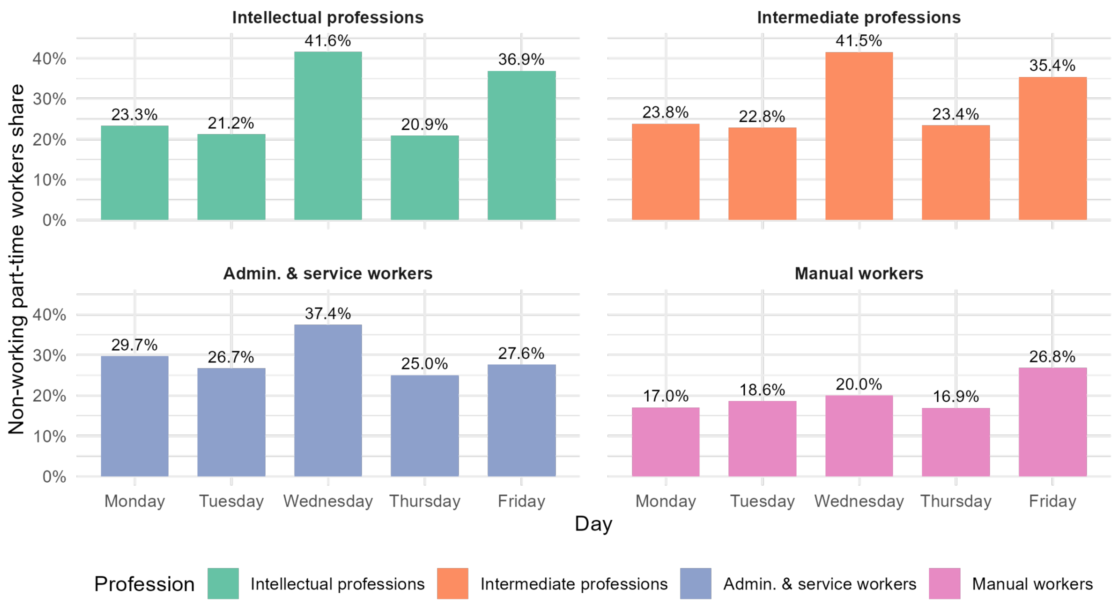


Note: The table reports the proportion of teleworkers among employed individuals aged 15 and over, by occupation and place of residence within Functional Urban Areas (FUAs) in the Auvergne–Rhône-Alpes region, where Lyon is located. Estimates are computed from the *Enquête Emploi en Continu*, fourth quarter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

Table 13 presents robustness checks of the results in Table 1, which estimate the daily shares of teleworkers working from home, now including date fixed effects. The estimates remain stable, confirming their robustness.

Table 13: Estimated share of teleworkers working from home by Weekday and municipality group

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
Variables			
Inactive population	0.9586***	0.9010***	1.028***
	(0.0336)	(0.0532)	(0.0575)
Teleworkers × Monday	0.4368***	0.6219***	0.4405
	(0.1432)	(0.1594)	(0.4242)
Teleworkers × Tuesday	0.2898*	0.4998***	0.0893
	(0.1519)	(0.1697)	(0.4278)
Teleworkers × Wednesday	0.5808***	0.7396***	0.6365+
	(0.1543)	(0.1709)	(0.4259)
Teleworkers × Thursday	0.2941**	0.5136***	0.1106
	(0.1438)	(0.1604)	(0.4253)
Teleworkers × Friday	0.7771***	0.9797***	0.6815+
	(0.1508)	(0.1650)	(0.4346)
Fixed-effects			
Date	Yes	Yes	Yes
Number of teleworked days (reference = 2.428)			
Inferred from estimates ($\sum_t \widehat{\beta}_t$)	2.379	3.355	1.958
Fit statistics			
Observations	126,031	57,919	68,112
Within R^2	0.74479	0.60958	0.84063

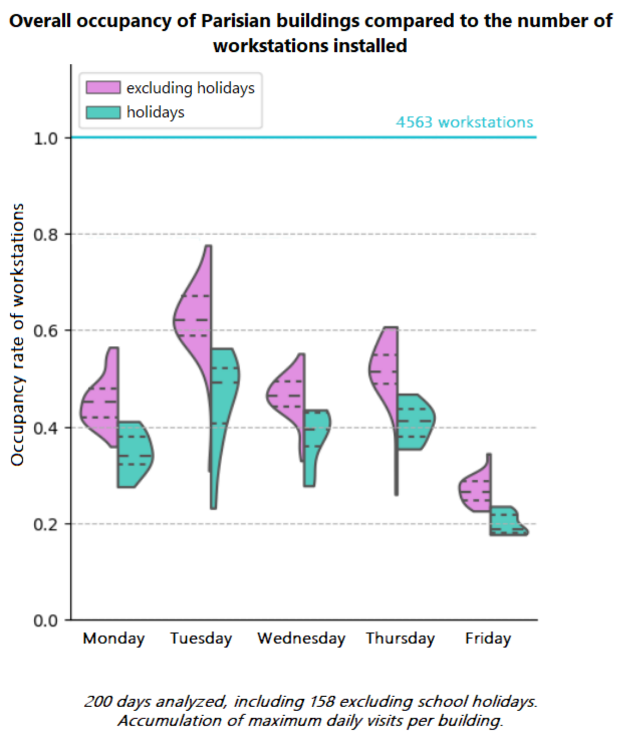
Note: Signif. codes: ***: 0.01, **: 0.05, *: 0.1, +: 0.15. Clustered standard-errors at the Iris zone level in parentheses. Estimations include date fixed effects. The reference number of teleworked days (conditional on teleworking) reported in the table, used to validate our results, is calculated from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

B.4 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 14 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).

Table 14: Classification of Retail and Service Activities

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

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 15, 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.

Table 15: Transaction count and value responses to telecommute shares

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Transaction count							
$\text{WFH}^{(\mathcal{H})}_{\text{telecommuters}}$	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)
$\text{WFH}^{(\mathcal{W})}_{\text{telecommuters}}$	-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)
$\text{WFH}^{(\mathcal{H})}_{\text{telecommuters}}$ × Public transp. disrupt.						0.561	
						(0.369)	
$\text{WFH}^{(\mathcal{W})}_{\text{telecommuters}}$ × 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							
$\text{WFH}^{(\mathcal{H})}_{\text{telecommuters}}$	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)
$\text{WFH}^{(\mathcal{W})}_{\text{telecommuters}}$	-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)
$\text{WFH}^{(\mathcal{H})}_{\text{telecommuters}}$ × Public transp. disrupt.						0.809*	
						(0.449)	
$\text{WFH}^{(\mathcal{W})}_{\text{telecommuters}}$ × 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, $|\theta_1/\theta_2|$, are computed using the Delta Method.

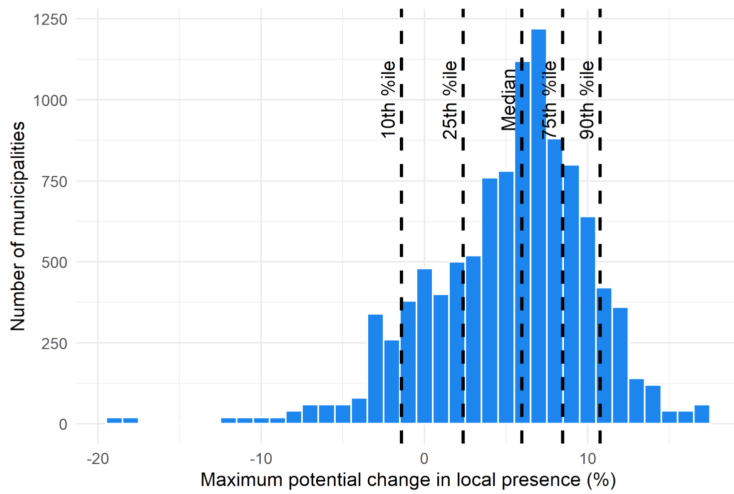
One might still be concerned that the identification relies on a mechanical relationship between home presence, $\text{WFH}^{(H)}$, and workplace absence, $\text{WFH}^{(W)}$. Both variables are constructed by projecting the same residential telework practices through commuting flows and multiplying by the same time component, $\widehat{\beta}_t$, making the two regressors structural mirrors of one another. This raises the question of where the independent variation needed to separately identify θ_1 and θ_2 comes from. If identification relies primarily on the cross-sectional differences between a municipality's residential telework intent and its workplace inflow, the model hinges on the distinction between "bedroom" and "employment-center" municipalities. To address this, we construct a measure of the maximum potential change in residential presence relative to a counterfactual scenario with no telework:

$$\Delta\%_{\text{presence}_i} = \frac{\text{Teleworkers}_i^{(\mathcal{H})} - \text{Teleworkers}_i^{(\mathcal{W})}}{\text{Inactive population}_i + \text{Workers}_i} \times 100 \tag{10}$$

where $\text{Teleworkers}_i^{(\mathcal{H})}$ and $\text{Teleworkers}_i^{(\mathcal{W})}$ are the numbers of teleworkers residing in and working in municipality i, respectively. The denominator includes the inactive population residing in i and all workers whose workplace is in i, providing a measure of the total potential local presence during working hours on weekdays in the counterfactual scenario with no telework. Positive values indicate municipalities where telework increases local presence, while negative values indicate areas where workplace absence dominates.

Figure 10 visualizes the distribution of $\Delta\%_{\text{presence}}$ across municipalities, highlighting substantial variation in potential telework-induced presence. Vertical lines mark key quantiles (10th, 25th, 50th, 75th, and 90th percentiles), illustrating the range of divergence between residential and workplace exposure. This measure provides a clear, intuitive indicator of where telework is most likely to shift local activity patterns and serves as the basis for robustness checks restricting the analysis to municipalities with large residential–workplace divergence.

The test consist in restricting the analysis to municipalities with different divergence intensity between residential and workplace exposure, based on the quantiles of Δ%presence. In particular, we restrict the sample to municipalities using the lower and upper tails of the $\Delta\%_{\text{presence}}$ distribution ($\leq$10% or $\geq$90% for model 1, $\leq$25% or $\geq$75% for model 2, $\leq$50% for model 3 and $\geq$50% for model 4). Table 16 shows that in municipalities with extreme divergences (columns 1–2), telework-induced home-presence significantly increases transactions ($\theta_1 = 0.96$ to 1.24, $p < 0.01$), while workplace-absence significantly reduces them ($\theta_2 = -1.19$ to -1.78, $p < 0.05$). This confirms that our estimates are not driven by mechanical mirroring between $\text{WFH}^{(\mathcal{H})}$ and $\text{WFH}^{(\mathcal{W})}$, but rather reflect causal effects of telework on local consumption. In the subsample where $\Delta\%_{\text{presence}}$ is below the median, we observe moderate to large variations in both $\text{WFH}^{(\mathcal{H})}$ and $\text{WFH}^{(\mathcal{W})}$. In contrast, in the subsample above the median, we focus mainly on highly residential areas, where the variation in $\text{WFH}^{(\mathcal{H})}$ is high and $\text{WFH}^{(\mathcal{W})}$ is low. This may explain the lack of significance of the coefficients in model 4: limited variation in the explanatory variable leads to larger standard errors, particularly in specifications with demanding fixed effects like ours.



Note: The histogram shows the percentage point increase in residential presence relative to a no-telework scenario. Positive values indicate municipalities where telework increases local presence, whereas negative values indicate areas where workplace presence dominates. Vertical lines (not shown) can mark key quantiles (median, 75th, 90th percentiles) for reference.

Figure 10: Distribution of maximum potential change in local presence due to telework

Table 16: Telework effects on transactions by home-presence and workplace-absence divergence

Sample	(1) $\leq$10% & $\geq$90%	(2) $\leq$25% & $\geq$75%	(3) $\leq$50%	(4) $\geq$ 50%
Panel A: Transaction count				
$\text{WFH}^{(\mathcal{H})}$	0.964***	1.24***	1.23***	0.273
	(0.269)	(0.341)	(0.299)	(1.33)
$\text{WFH}^{(\mathcal{W})}$	-1.19**	-1.78***	-1.84***	-0.722
	(0.489)	(0.521)	(0.433)	(1.32)
Fit statistics				
Observations	2,160	5,340	5,340	5,300
BIC	35,754.3	94,062.6	93,767.3	71,041.5
Panel B: Transaction value				
$\text{WFH}^{(\mathcal{H})}$	0.649	1.05***	0.984***	2.23
	(0.415)	(0.398)	(0.339)	(2.18)
$\text{WFH}^{(\mathcal{W})}$	-0.513	-1.40***	-1.35***	-0.638
	(0.475)	(0.524)	(0.441)	(2.12)
Fit statistics				
Observations	2,160	5,340	5,340	5,300
BIC	1,354,638.1	3,157,834.9	3,165,468.1	2,152,581.1

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. Each column restricts the sample to municipalities according to percentile in residential presence–workplace absence divergence, defined by the lower and upper tails of the $\Delta\%_{\text{presence}}$ distribution ($\leq$10% or $\geq$90% for model 1, $\leq$25% or $\geq$75% for model 2, $\leq$50% for model 3 and $\geq$50% for model 4).

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.

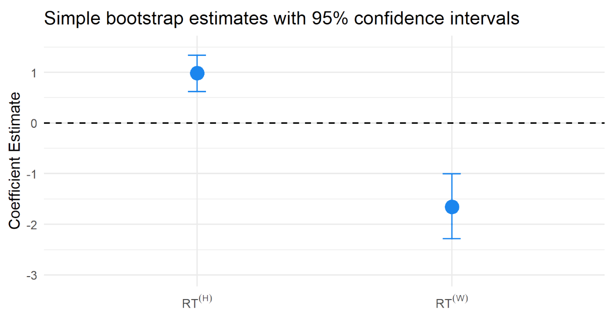
Rain reduces transactions by about 1% on average (significant at the 5% level), with stronger effects under heavier rainfall. Including this control leaves the estimated telework coefficients unchanged, suggesting limited confounding from weather conditions. Public transport disruption do not have a 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.

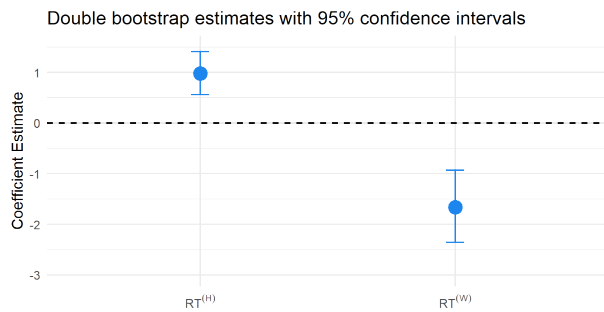
Our bootstrap procedure follows a rigorous multi-stage process designed to account for all potential sources of estimation uncertainty. Initially, we randomly resample clusters of municipalities with replacement to create alternative samples of our data. For each resampled dataset, we then re-estimate 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 11 and 12. Figure 11 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

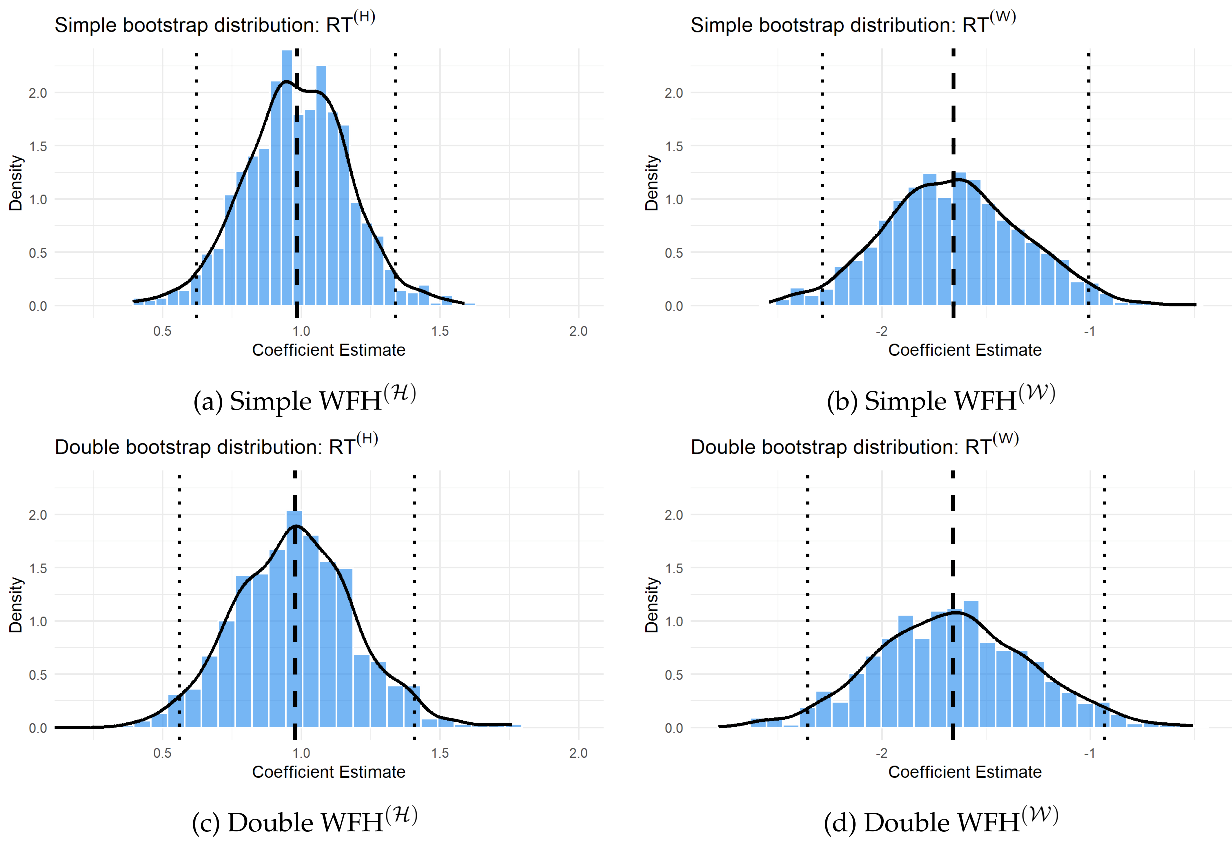


(b) Double

Note: This figure presents the estimates of a one percentage point increase in $\text{WFH}^{(\mathcal{H})}$ and $\text{WFH}^{(\mathcal{W})}$, 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 11: Comparison of bootstrapped coefficients and confidence intervals

Figure 12 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 WFH$^{(\mathcal{H})}$ (b) Simple WFH$^{(\mathcal{W})}$

(c) Double WFH$^{(\mathcal{H})}$ (d) Double WFH$^{(\mathcal{W})}$

Note: This figure presents the distribution of the estimates of a one percentage point increase in WFH$^{(\mathcal{H})}$ and WFH$^{(\mathcal{W})}$, 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 12: Distribution of bootstrapped coefficients across iterations

Two-way clustering of standard errors. Our baseline specification clusters standard errors at the municipality level, which may not fully account for correlations in the regression residuals. Because the main explanatory variables—the telework shares—include a common time component ($\widehat{\beta}_t$) and residuals may be correlated over time and across municipalities on the same day, we implement two-way clustering by municipality and date. This approach ensures that inference properly accounts for both temporal and cross-sectional dependencies.

Table 17 presents the results under this robust inference strategy. The estimated coefficients for θ_1 and θ_2 remain highly significant across all specifications, confirming that our headline conclusions are not sensitive to the clustering approach. For example, in our preferred specification (column 7), $\theta_1 = 0.985$ ($p < 0.01$) and $\theta_2 = -1.71$ ($p < 0.01$), with standard errors only marginally larger than in the baseline (0.388 vs. 0.213 for θ_1; 0.490 vs. 0.372 for θ_2).

Critically, the two-way clustering also ensures reliable inference for the work-to-home substitution rate, where uncertainty depends on the covariance between θ_1 and θ_2. The substitution rate is significantly below one for transaction frequency (e.g., 0.57 in column 7, with a 95% confidence interval of [0.248; 0.902]), while it is not statistically distinguishable from one for transaction value (e.g., 0.72, with a 95% confidence interval of [0.194; 1.248]).

Table 17: Robustness check: two-way clustering of standard errors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Transaction count							
$\text{WFH}^{(\mathcal{H})}$	1.15***	0.983**	1.15***	1.15***	1.15***	1.02**	0.985**
	(0.412)	(0.396)	(0.411)	(0.411)	(0.406)	(0.412)	(0.388)
$\text{WFH}^{(\mathcal{W})}$	-1.74***	-1.74***	-1.72***	-1.72***	-1.73***	-1.67***	-1.71***
	(0.495)	(0.494)	(0.490)	(0.489)	(0.497)	(0.487)	(0.490)
$\text{PT}^{(\mathcal{H})}$		1.66					1.66
		(1.06)					(1.04)
$\text{PT}^{(\mathcal{W})}$		1.47*					1.49*
		(0.776)					(0.777)
Rain			-0.008**				-0.009**
			(0.004)				(0.004)
Light rain				-0.008**			
				(0.004)			
Moderate rain				-0.014			
				(0.015)			
Public transp. disrupt.					0.009	-0.006	0.008
					(0.008)	(0.011)	(0.007)
$\text{WFH}^{(\mathcal{H})}$ × Public transp. disrupt.						0.720	
						(0.489)	
Public transp. disrupt. × $\text{WFH}^{(\mathcal{W})}$						-0.641	
						(0.444)	
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***
	(0.182)	(0.168)	(0.184)	(0.183)	(0.179)	(0.193)	(0.167)
Panel B: Transaction value							
$\text{WFH}^{(\mathcal{H})}$	1.064**	0.9659*	1.066**	1.067**	1.064**	0.9796*	0.9685*
	(0.5409)	(0.5403)	(0.5393)	(0.5394)	(0.5380)	(0.5424)	(0.5348)
$\text{WFH}^{(\mathcal{W})}$	-1.363**	-1.359**	-1.350**	-1.353**	-1.363**	-1.288**	-1.343**
	(0.5557)	(0.5797)	(0.5527)	(0.5520)	(0.5586)	(0.5326)	(0.5795)
$\text{PT}^{(\mathcal{H})}$		0.8377					0.8487
		(1.025)					(1.024)
$\text{PT}^{(\mathcal{W})}$		2.919***					2.934***
		(0.8219)					(0.8239)
Rain			-0.0058*				-0.0068*
			(0.0035)				(0.0035)
Light rain				-0.0059*			
				(0.0035)			
Moderate rain				-0.0118			
				(0.0179)			
Public transp. disrupt.					0.0063	0.0068	0.0061
					(0.0082)	(0.0173)	(0.0083)
$\text{WFH}^{(\mathcal{H})}$ × Public transp. disrupt.						0.7002**	
						(0.3235)	
Public transp. disrupt. × $\text{WFH}^{(\mathcal{W})}$						-0.7425**	
						(0.3170)	
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							
$\lvert\frac{\theta_1}{\theta_2}\rvert$	0.780***	0.711***	0.790***	0.788***	0.781***	0.761***	0.721***
	(0.268)	(0.267)	(0.272)	(0.27)	(0.267)	(0.275)	(0.269)

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

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 18, 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.

Table 18: Test of spatial heterogeneity: Transaction count and value responses to telework shares by zone group

	Transaction count (1)	Transaction value (2)
$WFH^{(\mathcal{H})}$	1.61***	0.469
	(0.587)	(0.750)
$WFH^{(\mathcal{W})}$	-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)
$WFH^{(\mathcal{H})} \times$ Rest of the core	-0.565	0.751
	(0.700)	(0.886)
$WFH^{(\mathcal{H})} \times$ Urban commuting zone	-1.05	0.132
	(0.713)	(0.858)
$WFH^{(\mathcal{H})} \times$ Rural commuting zone	-0.168	1.19
	(0.878)	(0.971)
$WFH^{(\mathcal{W})} \times$ Rest of the core	0.822	0.364
	(1.39)	(1.52)
$WFH^{(\mathcal{W})} \times$ Urban commuting zone	1.55	0.907
	(1.25)	(1.37)
$WFH^{(\mathcal{W})} \times$ 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.

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.

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 19. 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: $\text{WFH}_{it}^{(\mathcal{H})} = \widehat{\beta_{g(i)t}} \frac{\sum_{jk} \tau_{kg(i)} \text{Workers}_{ijk}}{\text{Workers}_i^{(\mathcal{H})}}$ and $\text{WFH}_{jt}^{(\mathcal{W})} = \frac{\sum_i \widehat{\beta_{g(i)t}} \sum_k \tau_{kg(i)} \text{Workers}_{ijk}}{\text{Workers}_j^{(\mathcal{W})}}$. 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.

Table 19: Transaction count and value responses to alternative telework shares (using $\widehat{\beta_{gt}}$)

	Transaction count			Transaction value		
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{WFH}^{(\mathcal{H})}_{\widehat{\beta_{gt}}}$	0.81***	0.67***	0.68***	0.73***	0.73**	0.73***
	(0.19)	(0.21)	(0.21)	(0.24)	(0.28)	(0.28)
$\text{WFH}^{(\mathcal{W})}_{\widehat{\beta_{gt}}}$	-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, $|\theta_1/\theta_2|$, are computed using the Delta Method.

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: $\text{WFH}^{(\mathcal{H})}_{it} = \widehat{\beta_{it}} \frac{\sum_{jk} \tau_{kg(i)} \text{Workers}_{ijk}}{\text{Workers}^{(\mathcal{H})}_i}$ and $\text{WFH}^{(\mathcal{W})}_{jt} = \frac{\sum_i \widehat{\beta_{it}} \sum_k \tau_{kg(i)} \text{Workers}_{ijk}}{\text{Workers}^{(\mathcal{W})}_j}$. 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 20 presents the results of this controlled measurement error test. We compare telework effects using alternative measures with systematically varying levels of measurement error: $\text{WFH}^{(\mathcal{H})}_{\text{scaled } \beta^{(1)}}$ and $\text{WFH}^{(\mathcal{W})}_{\text{scaled } \beta^{(1)}}$ contain higher measurement error than $\text{WFH}^{(\mathcal{H})}_{\text{scaled } \beta^{(2)}}$ and $\text{WFH}^{(\mathcal{W})}_{\text{scaled } \beta^{(2)}}$. 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.

Table 20: Sensitivity to measurement error: Transaction count and value responses to alternative telework specifications

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Transaction count						
$\text{WFH}^{(\mathcal{H})}_{\text{scaled } \beta^{(1)}}$	0.14	0.15	0.15*			
	(0.10)	(0.09)	(0.09)			
$\text{WFH}^{(\mathcal{W})}_{\text{scaled } \beta^{(1)}}$	-0.28	-0.44*	-0.42*			
	(0.26)	(0.26)	(0.26)			
$\text{WFH}^{(\mathcal{H})}_{\text{scaled } \beta^{(2)}}$				0.20**	0.22**	0.23**
				(0.10)	(0.10)	(0.10)
$\text{WFH}^{(\mathcal{W})}_{\text{scaled } \beta^{(2)}}$				-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						
$\text{WFH}^{(\mathcal{H})}_{\text{scaled } \beta^{(1)}}$	0.13	0.10	0.10			
	(0.10)	(0.11)	(0.11)			
$\text{WFH}^{(\mathcal{W})}_{\text{scaled } \beta^{(1)}}$	-0.69***	-0.61***	-0.59***			
	(0.18)	(0.18)	(0.18)			
$\text{WFH}^{(\mathcal{H})}_{\text{scaled } \beta^{(2)}}$				0.23**	0.21*	0.20*
				(0.11)	(0.11)	(0.11)
$\text{WFH}^{(\mathcal{W})}_{\text{scaled } \beta^{(2)}}$				-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, $|\theta_1/\theta_2|$, are computed using the Delta Method.

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 $\text{WFH}^{(\mathcal{H})}$ and $\text{WFH}^{(\mathcal{W})}$ 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.

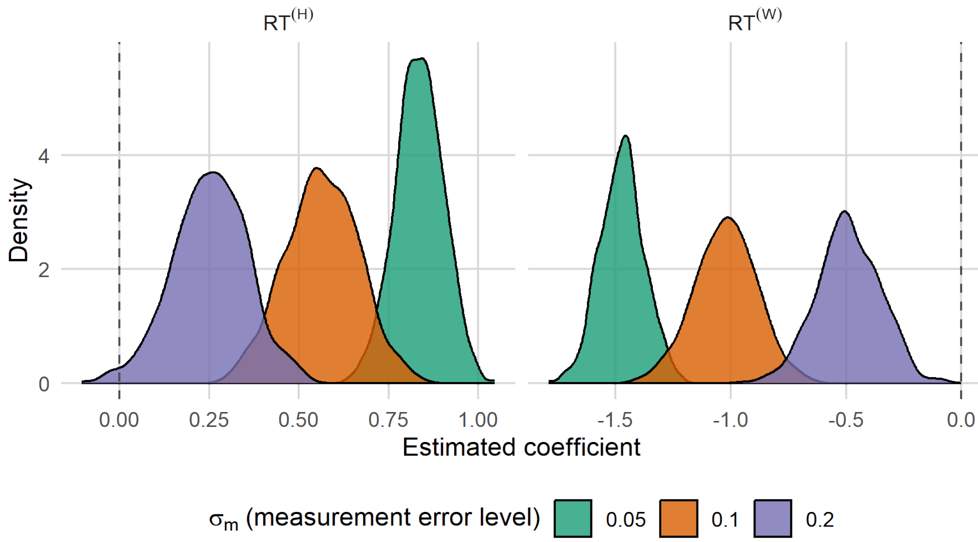
To quantitatively evaluate this sensitivity, we implement a controlled simulation approach that systematically introduces normally distributed random noise to our telework variables. For each variable, we generate measurement error proportional to specified error levels (σ_m) and create simulated variables according to: $\widetilde{\text{WFH}}_{it}^{(H)} = \text{WFH}_{it}^{(H)} + \varepsilon_{it}, \quad \varepsilon_{it} \sim \mathcal{N}\Big(0, \sigma_m \, \text{sd}(\text{WFH}_{it}^{(H)})\Big)$. 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 13 presents the results of our measurement error simulation analysis, revealing a clear systematic pattern:

- For $\text{WFH}^{(\mathcal{H})}$, the mean coefficient decreases from 0.836 ($\sigma_m = 0.05$) to 0.252 ($\sigma_m = 0.20$).
- For $\text{WFH}^{(\mathcal{W})}$, 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 13: Impact of measurement error on estimated coefficients for WFH$^{(\mathcal{H})}$ and WFH$^{(\mathcal{W})}$

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 residence–workplace–occupation matrices from the 1999, 2010, and 2015 population censuses, resulting in three separate instruments for each telework measure. The daily shift component captures deviations in 2022 daily working-from-home rates ($\widehat{\beta}_t$) relative to daily part-time day-off rates of executives ($\gamma_{k=\text{executives},t}$), whose average number of day-off days is similar to the pre-COVID average number of teleworked days. This component measures 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.

Together, the cross-sectional shares provide exogenous variation in historical exposure, while the shift term isolates unexpected deviations from baseline telework using external mobility data. This variation is plausibly unrelated to daily consumption, providing a credible source of exogenous variation to identify the causal effects of telework. The instrumental variables are computed as follows:

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

$$\text{IV}_{jt}^{(\mathcal{W})} = 100 \cdot \left(\widehat{\beta}_t - \gamma_{k=\text{executives},t}\right) \cdot \frac{\sum_{ik} \tau_{k,2017} \text{Workers}_{ijk,1999}}{\text{Workers}_{1999}^{(\mathcal{W})}} \tag{12}$$

Tables 21–23 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 $\text{WFH}^{(\mathcal{H})}$ and $\text{WFH}^{(\mathcal{W})}$ when using the 1999 instruments, and slightly lower effects with the 2010-2015 instruments. All effects are highly significant (see Figures 14 and 15 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.

Table 21: 2SRI results, 1999 instruments

Dependent Variables:	$WFH^{(\mathcal{H})}$	$WFH^{(\mathcal{W})}$	$WFH^{(\mathcal{H})}$	$WFH^{(\mathcal{W})}$	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)
$WFH^{(\mathcal{H})}$				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)
$WFH^{(\mathcal{W})}$			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 22: 2SRI results, 2010 instruments

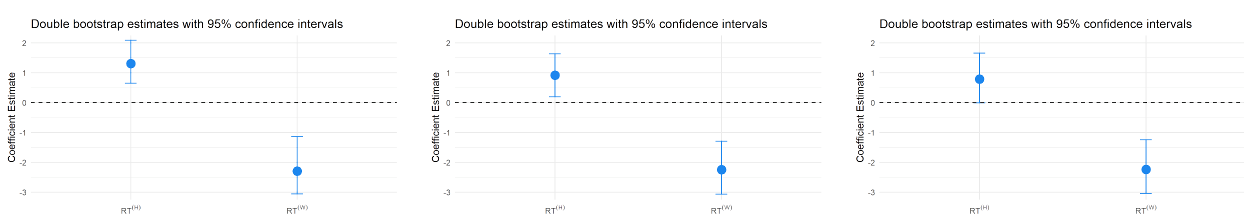
Dependent Variables:	$WFH^{(\mathcal{H})}$	$WFH^{(\mathcal{W})}$	$WFH^{(\mathcal{H})}$	$WFH^{(\mathcal{W})}$		Transaction count			Transaction value	
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Relevance test		First-stage		Baseline	Second-stage	Redundancy	Baseline	Second-stage	Redundancy
	OLS	OLS	OLS	OLS	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson
$IV^{(\mathcal{H})}_{2010}$	3.19***	-0.223	3.27***	-1.68***			-0.834			-0.297
	(0.791)	(0.560)	(0.699)	(0.536)			(1.27)			(1.87)
$IV^{(\mathcal{W})}_{2010}$	-2.16***	0.969**	-2.54***	1.96***			-0.086			-0.519
	(0.536)	(0.472)	(0.495)	(0.470)			(1.03)			(1.37)
$WFH^{(\mathcal{H})}$				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)
$WFH^{(\mathcal{W})}$			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)
$Residuals^{(\mathcal{H})}$						0.834*			0.681	
						(0.451)			(0.800)	
$Residuals^{(\mathcal{W})}$						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 23: 2SRI results, 2015 instruments

Dependent Variables:	$WFH^{(\mathcal{H})}$	$WFH^{(\mathcal{W})}$	$WFH^{(\mathcal{H})}$	$WFH^{(\mathcal{W})}$	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
$IV_{2015}^{(\mathcal{H})}$	2.41***	-0.122	2.46***	-1.21**			-0.938			-0.590
	(0.697)	(0.499)	(0.632)	(0.494)			(0.890)			(1.43)
$IV_{2015}^{(\mathcal{W})}$	-1.58***	0.796*	-1.89***	1.51***			0.066			-0.161
	(0.469)	(0.454)	(0.478)	(0.492)			(0.694)			(0.963)
$WFH^{(\mathcal{H})}$				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)
$WFH^{(\mathcal{W})}$			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						

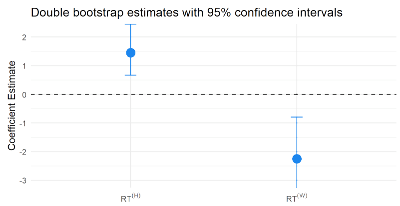
Note: Signif. codes: ***: 0.01, **: 0.05, *: 0.1. Clustered standard-errors at the municipality level in parentheses. All specifications include municipality and date-by-zone type fixed effects. The table presents a series of estimations examining the relationship between teleworking intensity and local 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.



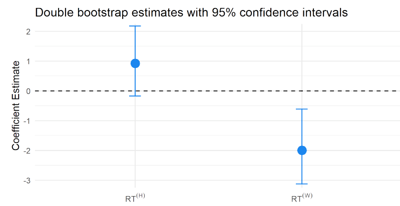
(a) 1999 Instruments (b) 2010 Instruments (c) 2015 Instruments

Note: These panels present the estimated effects of a one-percentage-point increase in $WFH^{(\mathcal{H})}$ and $WFH^{(\mathcal{W})}$ 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.

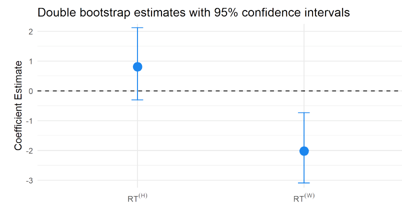
Figure 14: Bootstrapped 2SRI coefficients and confidence intervals for transaction counts by instrument year



(a) 1999 Instruments



(b) 2010 Instruments



(c) 2015 Instruments

Note: This figure presents the estimated effects of a one-percentage-point increase in $\text{WFH}^{(\mathcal{H})}$ and $\text{WFH}^{(\mathcal{W})}$ 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 15: 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:

$$Y_{it} = \exp\left[\theta_1 \text{TE}_i^{(\mathcal{H})} + \theta_2 \text{TE}_i^{(\mathcal{W})} + \theta_3 \log(\text{Pop}_i) + \theta_4 \log(\text{Workers}_i) + \delta_g + \gamma_t + \epsilon_{it}\right]. \tag{13}$$

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 $\text{TE}_i^{(\mathcal{H})}$, which captures the potential for telework at the place of residence (interpreted as a proxy for increased home presence), and $\text{TE}_i^{(\mathcal{W})}$, 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 24. The coefficients for $\text{TE}_i^{(\mathcal{H})}$ and $\text{TE}_i^{(\mathcal{W})}$ 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.

Table 24: Spatial variation analysis: Transaction count and value responses to telework potential

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Transaction count							
Constant	3.62***	-1.19***					
	(0.463)	(0.376)					
$\text{TE}^{(\mathcal{H})}$	4.10	2.36	2.36	2.36*			
	(3.47)	(1.51)	(1.51)	(1.29)			
$\text{TE}^{(\mathcal{W})}$	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)	
$\text{WFH}^{(\mathcal{H})}$					3.92	3.96*	1.15***
					(2.55)	(2.12)	(0.226)
$\text{WFH}^{(\mathcal{W})}$					-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)					
$\text{TE}^{(\mathcal{H})}$	2.47	1.35	1.35	2.95*			
	(3.39)	(1.71)	(1.71)	(1.61)			
$\text{TE}^{(\mathcal{W})}$	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)	
$\text{WFH}^{(\mathcal{H})}$					1.98	4.84*	1.06***
					(2.85)	(2.63)	(0.269)
$\text{WFH}^{(\mathcal{W})}$					-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.

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 addressing three policy-relevant questions, with results shown in Figures 16–23.

First, we examine the aggregate effect of telework on local economic activity when simultaneously considering both residential and workplace impacts. As illustrated in Figures 17–21, 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.

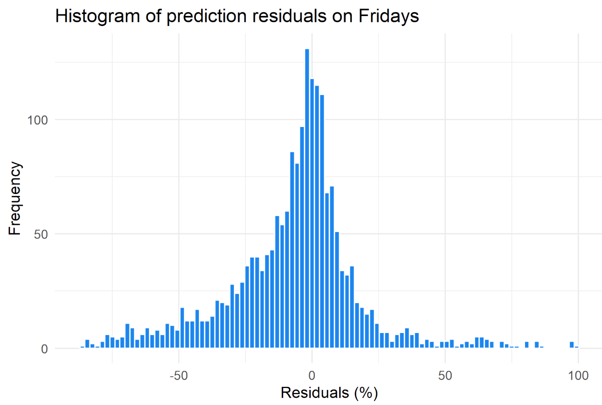
Second, we investigate how this net effect varies across different days of the week, reflecting the temporal heterogeneity in telework adoption patterns. Figure 16 demonstrates the model's predictive accuracy through the distribution of prediction errors, providing the foundation for our day-specific analyses. The patterns observed in Figures 17–21 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 22 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 23, which shows the percentage of municipalities experiencing declines in transaction values.

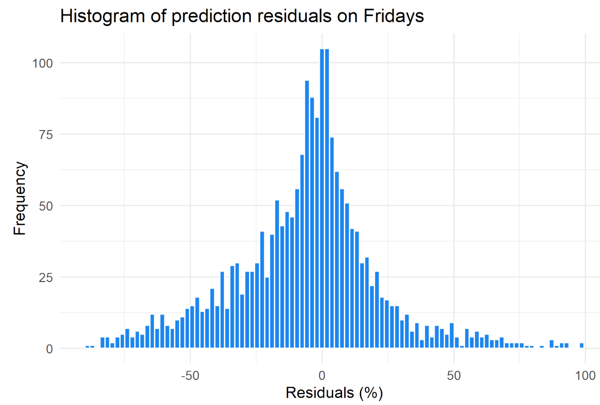
Our analytical approach integrates several complementary elements that build upon one another. The counterfactual simulation framework (Figure 16) demonstrates the model's predictive accuracy and provides the foundation for our subsequent analyses. The day-specific results (Figures 17–21) reveal important temporal patterns in telework impacts, while our spatial decomposition analysis (Figures 22 and 23) 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.

C.3.1 Results



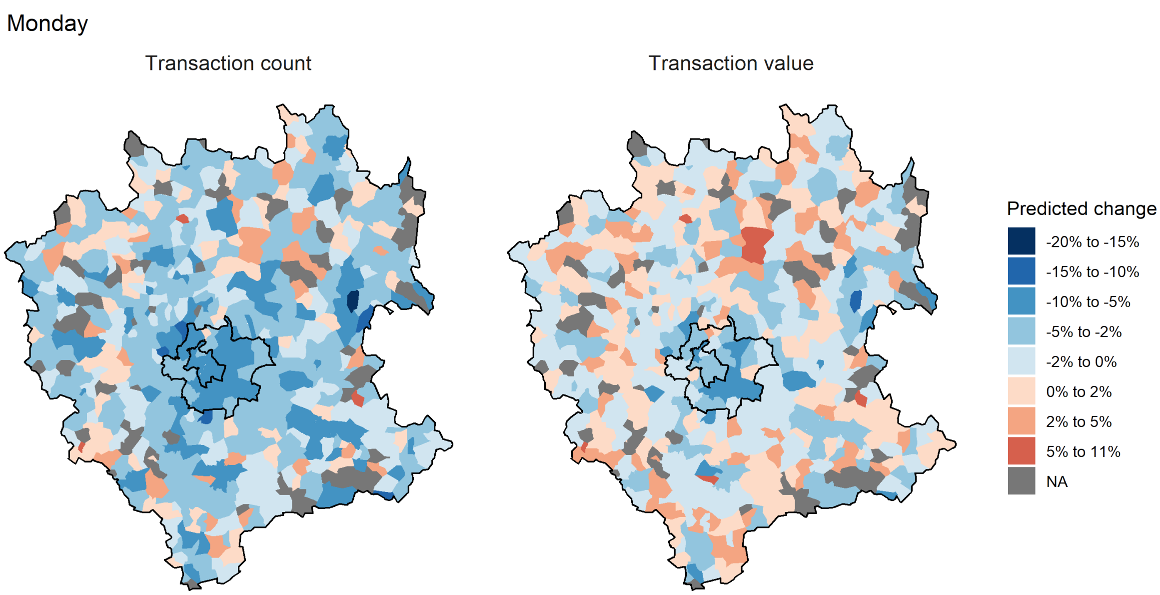
(a) Transaction count model



(b) Transaction value model

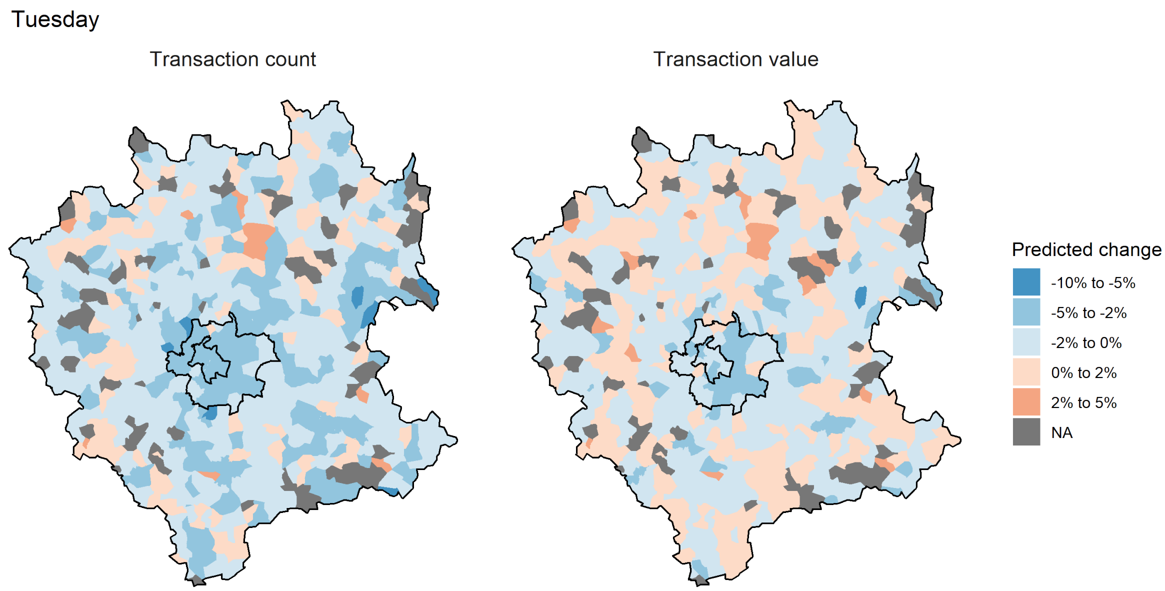
Note: This figure presents the distribution of the prediction error in percentage to Poisson Maximum Likelihood specifications, with the whole set of controls, and fixed effects for municipality and date-by-zone type.

Figure 16: Residuals distribution on Fridays



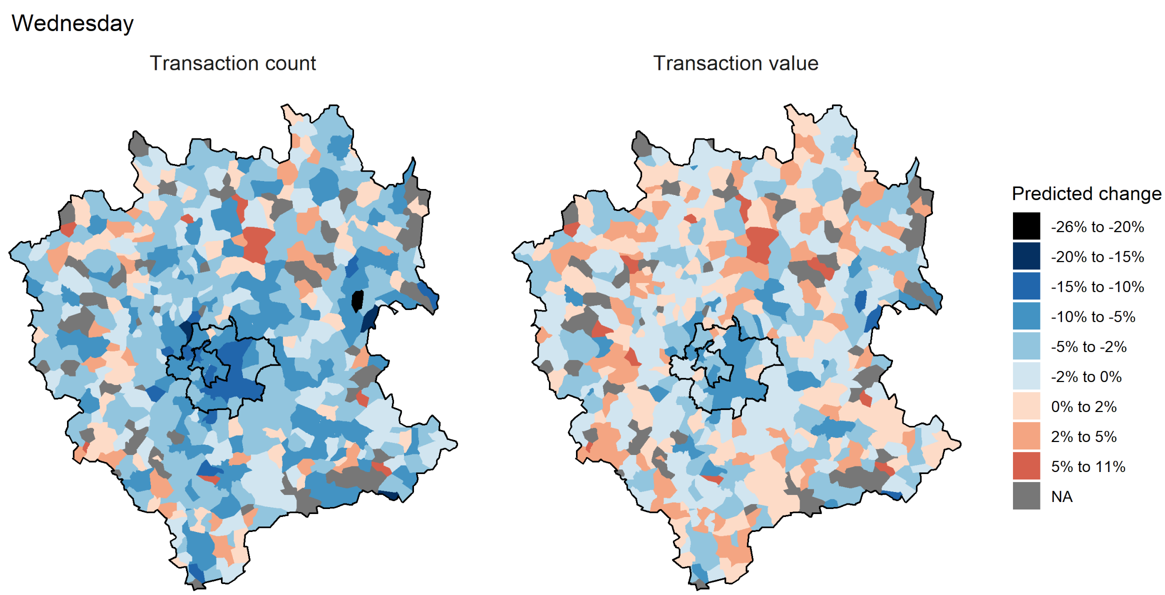
Note: The two figures show the average effect of telework on Mondays, measured as the percentage change in transaction count and transaction value, respectively. This is computed as $(\hat{y}_i - \hat{y}_i^0)/\hat{y}_i^0$, where $\hat{y}_i$ denotes the model-predicted values averaged over Mondays, and $\hat{y}_i^0$ 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 17: Average effect of telework on Monday



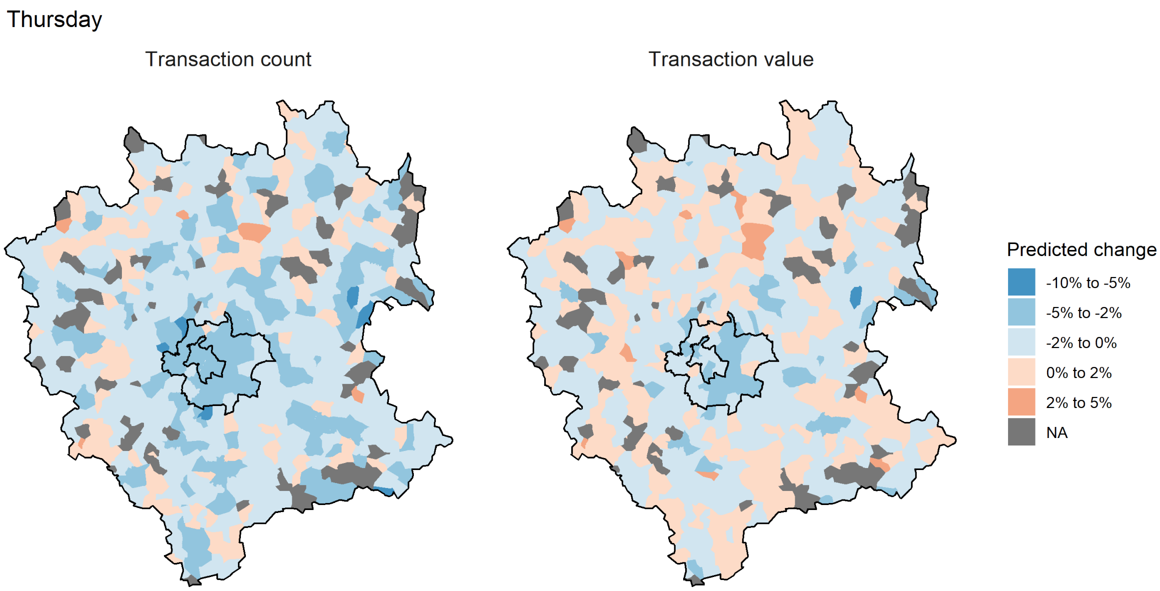
Note: The two figures show the average effect of telework on Tuesdays, measured as the percentage change in transaction count and transaction value, respectively. This is computed as $(\hat{y}_i - \hat{y}_i^0)/\hat{y}_i^0$, where $\hat{y}_i$ denotes the model-predicted values averaged over Tuesdays, 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 18: Average effect of telework on Tuesday



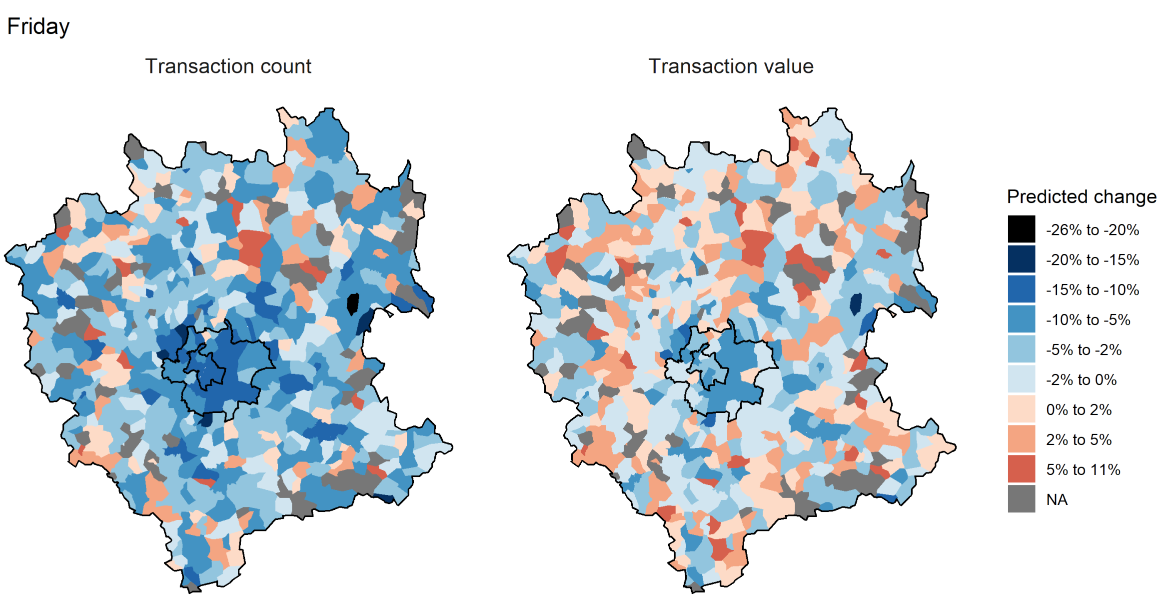
Note: The two figures show the average effect of telework on Wednesdays, measured as the percentage change in transaction count and transaction value, respectively. This is computed as $(\hat{y}_i - \hat{y}_i^0)/\hat{y}_i^0$, where $\hat{y}_i$ denotes the model-predicted values averaged over Wednesdays, 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 19: Average effect of telework on Wednesday



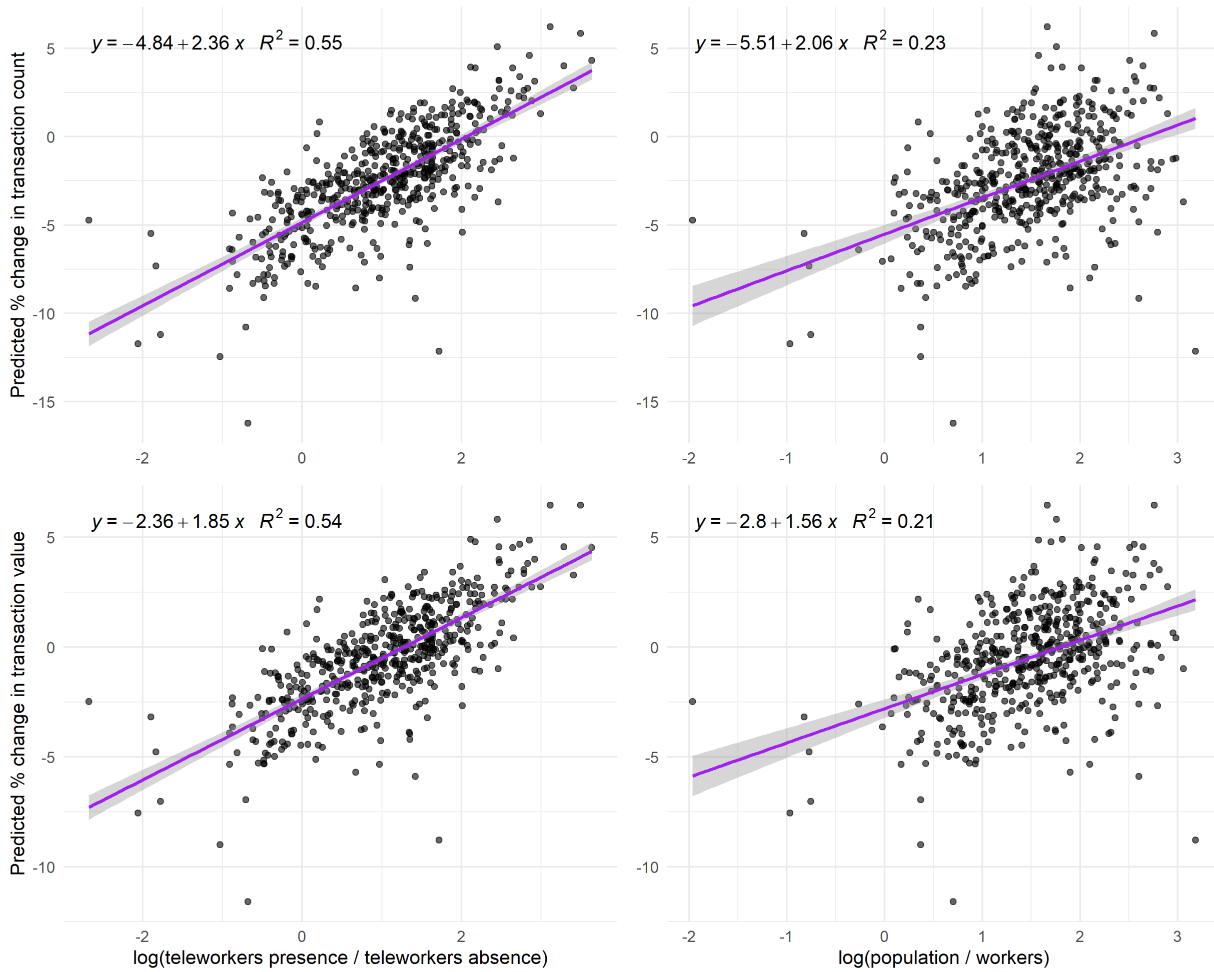
Note: The two figures show the average effect of telework on Thursdays, measured as the percentage change in transaction count and transaction value, respectively. This is computed as $(\hat{y}_i - \hat{y}_i^0)/\hat{y}_i^0$, where $\hat{y}_i$ denotes the model-predicted values averaged over Thurdays, 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 20: Average effect of telework on Thursday



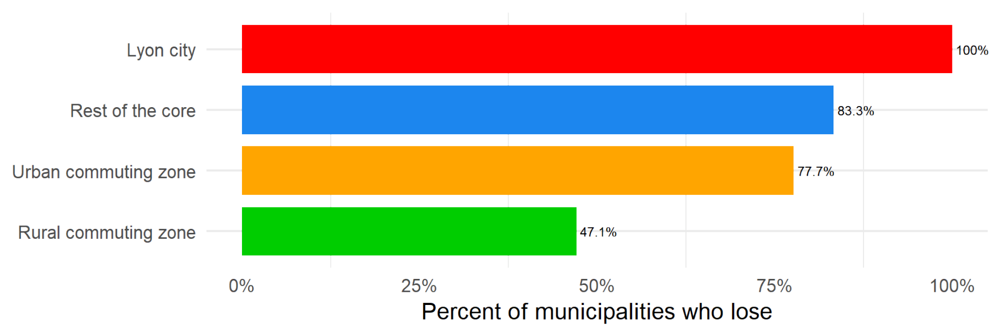
Note: The two figures show the average effect of telework on Fridays, measured as the percentage change in transaction count and transaction value, respectively. This is computed as $(\hat{y}_i - \hat{y}_i^0)/\hat{y}_i^0$, where $\hat{y}_i$ denotes the model-predicted values averaged over Fridays, and $\hat{y}_i^0$ 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 21: 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 22: 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 23: Percent of municipalities who lose, per zone group within the FUA

C.3.2 Statistical significance test on the consumption rate and aggregated telework net effects

To robustly assess the uncertainty surrounding our estimates, we implement a clustered bootstrap procedure with 500 iterations. In each iteration, municipalities are resampled with replacement, and the Poisson model is re-estimated using the Pseudo-Maximum Likelihood method. This approach captures uncertainty from three sources: (1) coefficient estimation ($\hat{\theta}_1$, $\hat{\theta}_2$), (2) prediction variability ($\hat{y}_{it}$), and (3) spatial heterogeneity across municipalities. We compute two substitution rates, in percentage points ($|\hat{\theta}_1/\hat{\theta}_2|$) and in units (scaling by worker populations), and weighted average effects for each spatial zone and the entire FUA. This method provides confidence intervals that account for all sources of uncertainty.

Bootstrap procedure. The bootstrap procedure is implemented through the following steps:

1. Draw a sample of 532 municipalities with replacement, including their full time series of transactions and telework shares.
2. Estimate coefficients θ_1 and θ_2.
3. Compute and store the consumption substitution rates, as defined as the relative marginal effects, both in percentage points and in units:
   (a) In percentage points : $|\frac{\widehat{\theta_1}}{\widehat{\theta_2}}|$
   (b) In units : $\left|\frac{\exp\left[\frac{\widehat{\theta_1}}{\text{Workers}^{(\mathcal{H})}}\right]-1}{\exp\left[\frac{\widehat{\theta_2}}{\text{Workers}^{(\mathcal{W})}}\right]-1}\right|$
4. For each municipality, compute the average $\Delta_i\% = \frac{1}{T}\sum_t \frac{\hat{y}_{it}-\hat{y}^0_{it}}{\hat{y}^0_{it}}$ (telework effect), and store the iteration results.
5. Compute the weighted average of $\Delta_i\%$ for each group (Lyon, inner urban ring, outer urban/rural ring), using average municipalities' transaction levels as weights, and store the iteration results.
6. Compute the weighted average of $\Delta_i\%$ for the entire FUA, using average municipalities' transaction levels as weights, and store the iteration results.
7. Repeat steps (1) to (5) 500 times.
8. This yields the distribution of results at each level of observation (municipality, municipality group, and overall Lyon FUA).

Distribution of estimates over all iterations. Table 25 shows the statistic descriptive of the computed variables over all iterations. There is no outlier.

Distribution of the net aggregated effect of telework. Table 26 presents the average effect of telework on transaction frequency and value, together with 90% confidence intervals, by municipality group and for the Lyon FUA as a whole. The estimated effects on transaction frequency are negative and statistically significant for Lyon city, the rest of the urban core, and the urban commuting zone. In contrast, no statistically significant effects are found for transaction value in

Table 25: Descriptive statistics of estimates over all iterations

Variable	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	N
Panel A: Transaction frequency							
CSR in pp	0.18	0.50	0.59	0.61	0.70	1.33	500
CSR in units	0.20	0.52	0.62	0.64	0.72	1.38	500
Δ_i%	-27.46	-4.26	-1.91	-2.13	0.29	11.93	168,149
Δ_g%	-17.15	-6.86	-4.41	-4.75	-2.46	5.01	2,000
Δ%	-14.43	-7.37	-5.33	-5.23	-3.13	3.46	500
Panel B: Transaction value							
CSR in pp	0.21	0.62	0.74	0.78	0.90	2.23	500
CSR in units	0.23	0.64	0.77	0.82	0.93	2.14	500
Δ_i%	-23.44	-2.21	-0.13	-0.29	1.85	15.07	168,149
Δ_g%	-14.83	-3.97	-2.02	-2.09	-0.07	7.81	2,000
Δ%	-11.92	-4.28	-2.52	-2.37	-0.34	5.46	500

Note: The table reports the bootstrap distribution (500 iterations) of the estimated consumption substitution rates—expressed in percentage points of workers and in teleworker levels—together with the estimated net telework effect (in percent) at the municipality, municipality-group, and Lyon FUA levels.

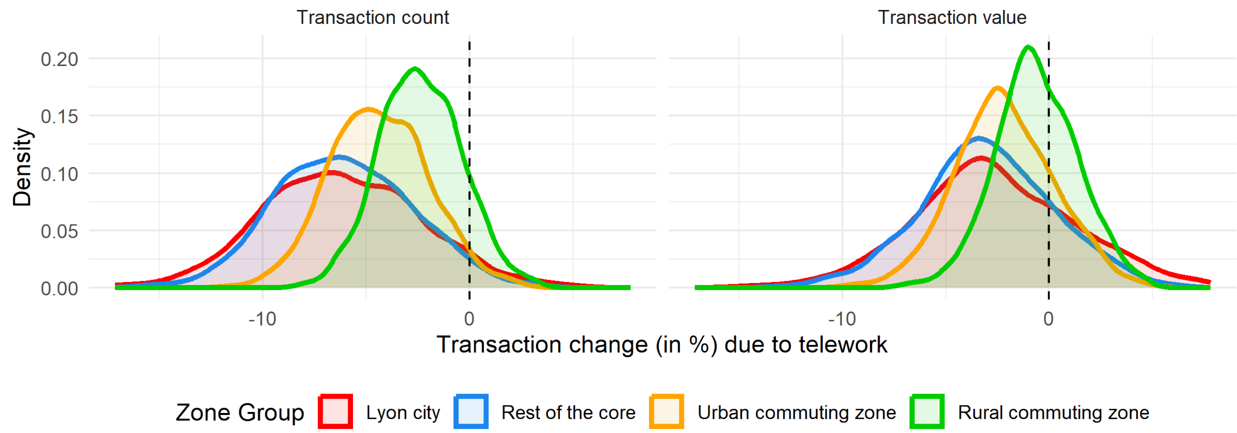
any group, as the 90% confidence intervals include zero. Aggregating across all municipalities, telework is associated with a statistically significant reduction in transaction frequency for the Lyon FUA overall, while transaction value remains unaffected. Figure 24 displays the bootstrap distributions of the estimates.

Table 26: Bootstrap aggregated effects of telework (in % change of transactions)

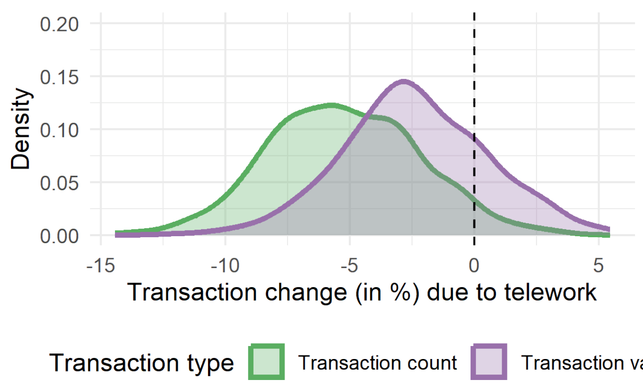
	Mean	90% CI
Panel A: Transaction frequency		
Lyon city	-6.162	[-12.030; -0.098]
Rest of the core	-6.075	[-11.172; -0.641]
Urban commuting zone	-4.383	[-8.015; -0.462]
Rural commuting zone	-2.372	[-5.589; 0.779]
All FUA	-5.231	[-9.924; -0.382]
Panel B: Transaction value		
Lyon city	-2.615	[-8.621; 4.044]
Rest of the core	-2.992	[-8.142; 2.276]
Urban commuting zone	-2.155	[-6.048; 1.856]
Rural commuting zone	-0.613	[-3.786; 2.774]
All FUA	-2.370	[-7.057; 2.634]

Note: The table reports the bootstrap aggregated average effect of telework on transaction frequency and value by municipality group and for the entire Lyon FUA, together with 90% confidence intervals computed over 500 iterations.

Distribution of the average consumption substitution rate. Table 27 reports the average consumption substitution rate, measured both in percentage points and in levels, with 90% confidence intervals. The estimated substitution rates for transaction frequency are 0.614 (percentage points) and 0.641 (units), with 90% confidence intervals ranging from approximately 0.39 to 0.93. Because



(a) By municipalities' group



(b) Over the Lyon FUA [1ex]

Note: The Figures display the bootstrap distribution (500 iterations) of the estimated net telework effects (in percent) on transaction frequency and value within each municipality-group (subfigure A), and Lyon FUA levels (subfigure B).

Figure 24: Bootstrap distribution of the average daily aggregated effect of telework

the entire confidence interval lies below unity, this indicates incomplete consumption substitution: when telework reduces workplace transactions, only about 61–64% of the lost activity is compensated by home consumption. For transaction value, the estimates are 0.781 (percentage points) and 0.815 (units), with wider 90% confidence intervals [0.45; 1.36]. Because the confidence interval includes 1, we cannot conclude that substitution is statistically incomplete for transaction value. In other words, the observed reallocation of spending may be consistent with full substitution in terms of transaction value.

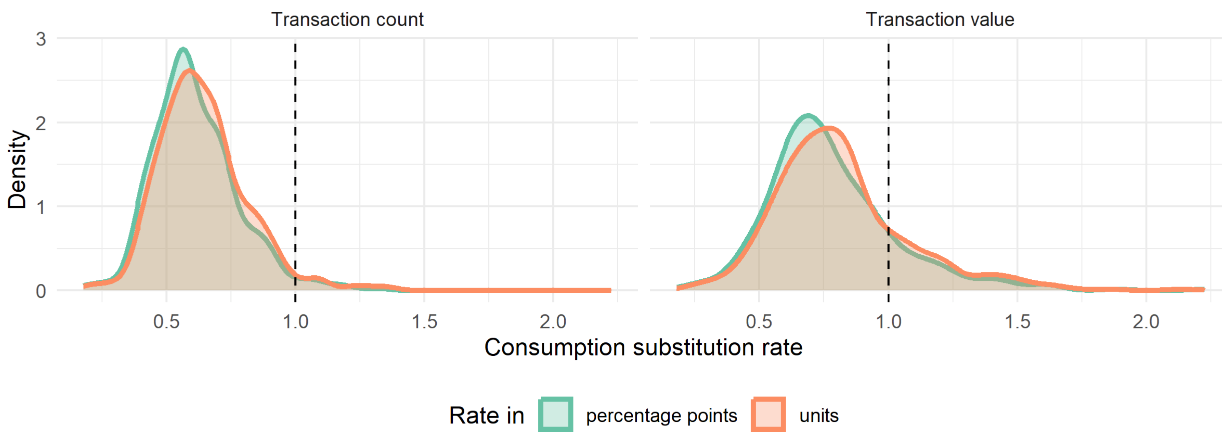
Figure 25 displays the bootstrap distribution of the estimates, confirming the variability and statistical significance patterns observed in the table.

Distribution of the net effect of telework by municipality. Table 28 presents the distribution of average telework effects at the municipality level, separately for transaction frequency (Panel A) and transaction value (Panel B). For each outcome, the table distinguishes between the full sample of municipalities and the subset with statistically significant effects, positive and negative, at the

Table 27: Bootstrap municipalities' consumption substitution rate

	Mean	90% CI
Panel A: Transaction frequency		
percentage points	0.614	[0.392; 0.904]
units	0.641	[0.408; 0.931]
Panel B: Transaction value		
percentage points	0.781	[0.450; 1.263]
units	0.815	[0.466; 1.355]

Note: The table reports the bootstrap average work-to-home consumption substitution rates (for both transaction count and value), expressed both in percentage points of workers and in teleworker levels, computed over 500 iterations, along with their 90% confidence intervals.



[1ex]
Note: The figure displays the bootstrap distributions of work-to-home consumption substitution rates (for both transaction count and value), expressed both in percentage points of workers and in teleworker levels, computed over 500 iterations.

Figure 25: Bootstrap distribution of the average municipalities' consumption substitution rate

10% level.

For transaction frequency (Panel A), effects across all municipalities range from -15.61% to 6.35%, with a median of -2.08%, indicating a modest overall reduction associated with telework. Among the 168 municipalities with significant effects, 26 exhibit positive effects (median 3.16%) while 142 show negative effects (median -4.97%), showing that negative significant effects are substantially more frequent than positive ones.

For transaction value (Panel B), effects range from -11.55% to 6.78%, with a median near zero (-0.20%), suggesting a limited overall impact. Of the 70 municipalities with significant effects, 46 display positive effects (median 3.35%) and 24 display negative effects (median -4.76%), indicating that positive significant effects are slightly more common than negative ones, albeit in a smaller sample.

Table 28: Bootstrap distribution of average telework effects across municipalities

Sample	Min.	1st Qu.	Median	3rd Qu.	Max.	N
Panel A: Transaction frequency						
All	-15.608	-3.742	-2.077	-0.252	6.350	532
Significant positive	1.383	2.768	3.157	4.150	6.350	26
Significant negative	-15.608	-6.431	-4.966	-3.928	-2.446	142
Panel B: Transaction value						
All	-11.549	-1.680	-0.204	1.230	6.784	532
Significant positive	1.815	2.632	3.345	4.218	6.784	46
Significant negative	-11.549	-5.391	-4.763	-4.192	-2.372	24

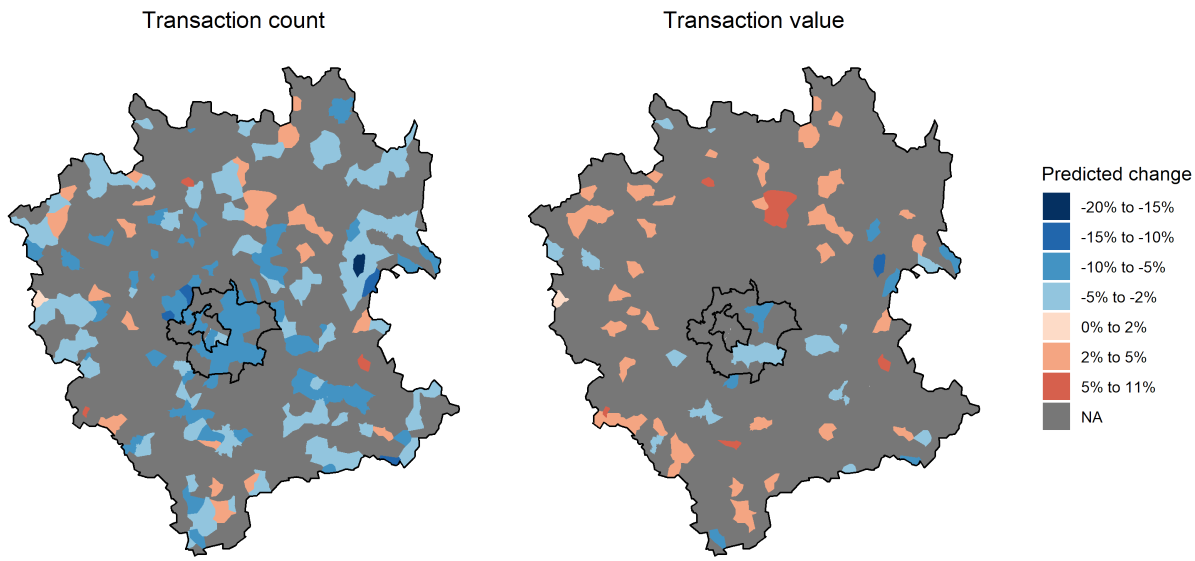
Note: The table reports the bootstrap distribution of average telework effects across municipalities. Panel A refers to transaction frequency, while Panel B refers to transaction value. For each panel, "Significant positive" and "Significant negative" indicate the subset of municipalities where the effect is statistically significant at the 10% level and positive or negative, respectively.

Table 29: Distribution of municipalities with significant average telework effect

		Significant	
	All	> 0	< 0
Panel A: Transaction frequency			
Lyon city	4	0	4
	(44.4%)	(0.0%)	(44.4%)
Rest of the core	13	0	13
	(43.3%)	(0.0%)	(43.3%)
Urban commuting zone	58	1	57
	(34.9%)	(0.6%)	(34.3%)
Rural commuting zone	93	25	68
	(28.4%)	(7.6%)	(20.8%)
Panel B: Transaction value			
Lyon city	0	0	0
	(0.0%)	(0.0%)	(0.0%)
Rest of the core	4	0	4
	(13.3%)	(0%)	(13.3%)
Urban commuting zone	10	3	7
	(6.0%)	(1.8%)	(4.2%)
Rural commuting zone	56	43	13
	(17.1%)	(13.1%)	(4.0%)

Note: The table reports the number of municipalities exhibiting a statistically significant average telework effect by zone group (at least at the 10% significance level). Columns "All", "> 0", and "< 0" respectively indicate the total number of municipalities with a significant telework effect, those with a significant positive effect, and those with a significant negative effect. Panel A refers to transaction frequency, while Panel B refers to transaction value. Percentages reported in parentheses are computed relative to the total number of municipalities within each zone group.

Distribution of the net effect of telework by municipality group. Table 29 examine the spatial distribution of significant telework effects across municipality groups. For transaction frequency



Note: The maps show municipalities with statistically significant average telework effects on transaction frequency (left panel) and transaction value (right panel). Only municipalities with significant effects at the 10% level are colored, with positive and negative effects distinguished by the color scale. Municipalities shown in grey exhibit non-significant effects.

Figure 26: Statistically significant telework effect on transaction frequency and value

(Panel A), the proportion of municipalities with significant effects is highest in Lyon city (44.4%) and the rest of the urban core (43.3%), but the number of municipalities is small. Urban commuting zones show a slightly lower share (34.9%), while rural commuting zones have the lowest proportion of significant effects (28.4%), despite representing the largest number of municipalities. Interestingly, negative significant effects dominate across all zones, with positive significant effects almost exclusively observed in rural areas.

For transaction value (Panel B), significant effects are again largely concentrated in rural commuting zones. In Lyon city, no municipality exhibits a significant effect of telework, and only a few municipalities in the rest of the core and urban commuting zones show significant effects. Rural areas display the highest number and share of significant positive effects (13.1%) as well as some negative effects (4.0%). These patterns suggest that the impact of telework on transaction values is spatially heterogeneous, with rural municipalities more likely to experience substantial changes, particularly positive ones, compared to dense urban cores.

To complement our understanding of the spatial effects of telework, Figure 26 shows, on maps, the distribution of statistically significant average telework effects on transaction frequency and transaction value across municipalities.

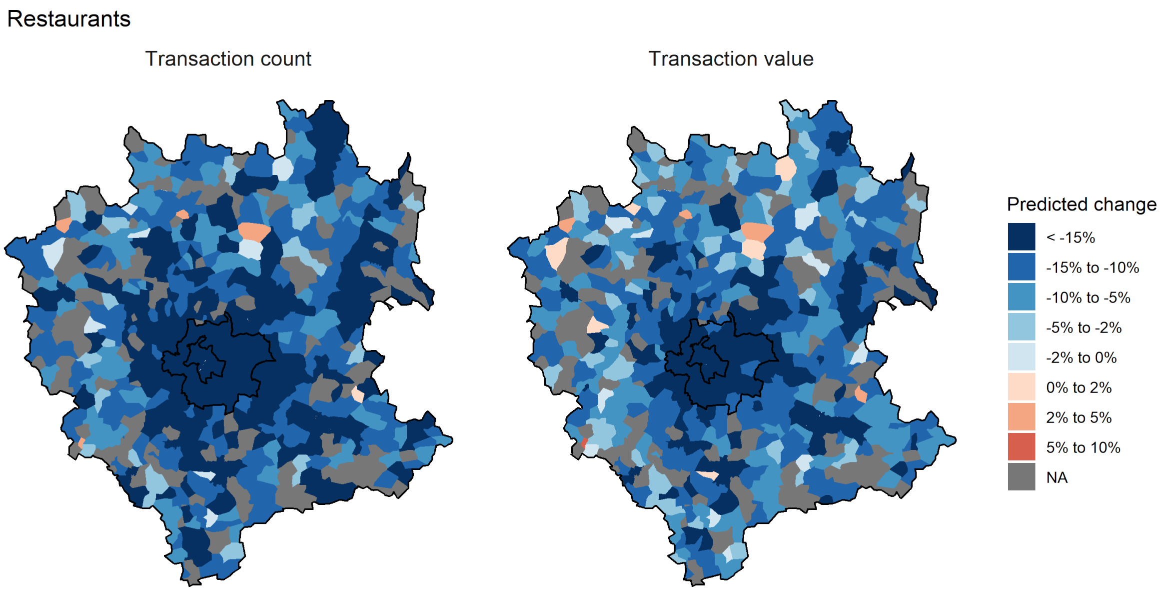
C.4 Sectoral Heterogeneity in Telework Effects

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 Net Effects of Telework by Sector

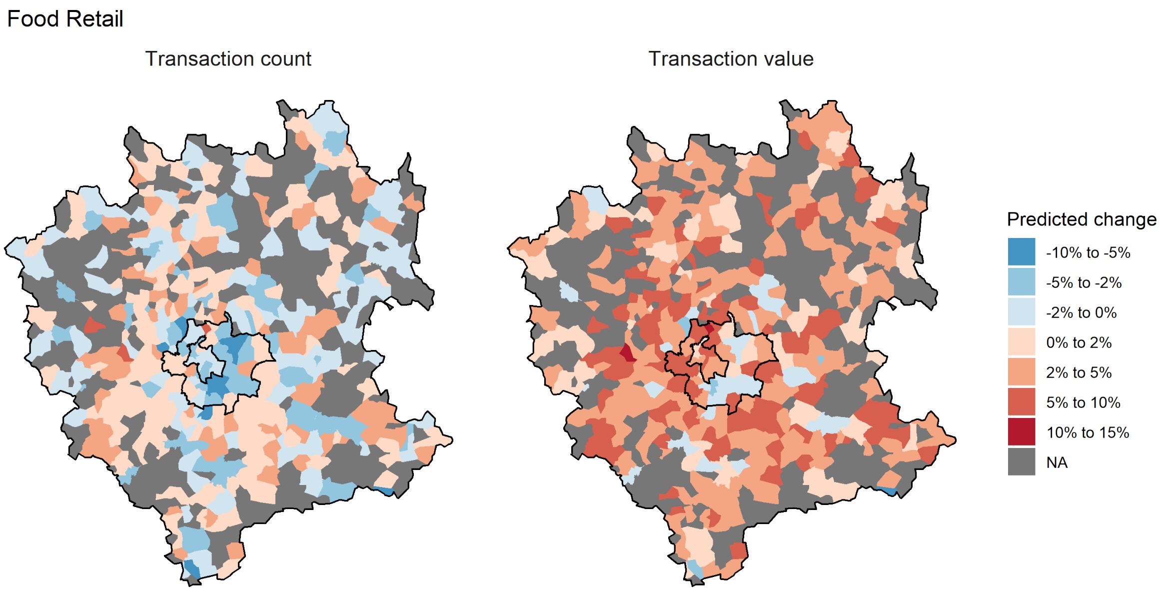
To quantify the overall economic impact of telework on each sector, we conduct counterfactual analyses that compare actual consumption patterns with those predicted under a zero-telework scenario. Figures 27 through 30 present the estimated effects of telework on transaction counts and values for four key sectors: Restaurants, Food Retail, General Retail, and Bars and Drinks. The Restaurants sector (Figure 27) 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 28) 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 29) 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 30) 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.



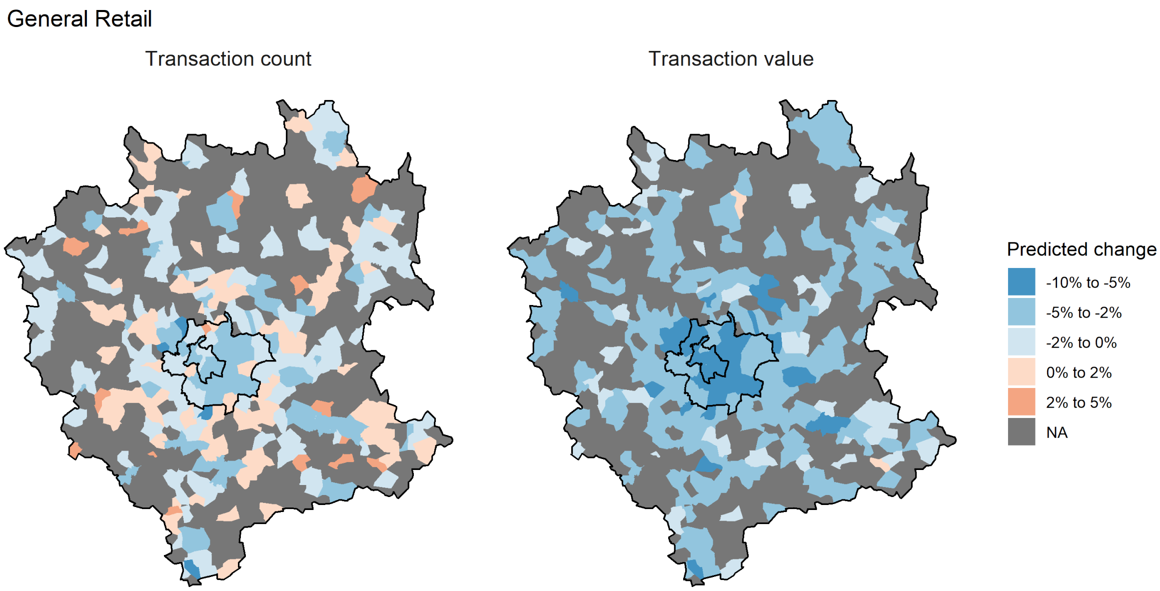
Note: The two figures show the effect of telework on transaction counts and transaction values, respectively, in the sector $s = \textit{Restaurants}$. This is computed as the weekly average of the ratio $(\tilde{y}_{ids} - \tilde{y}^0_{ids})/\tilde{y}^0_{ids}$, where $\tilde{y}_{ids}$ denotes the model-predicted 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 27: Effect of telework in Restaurants



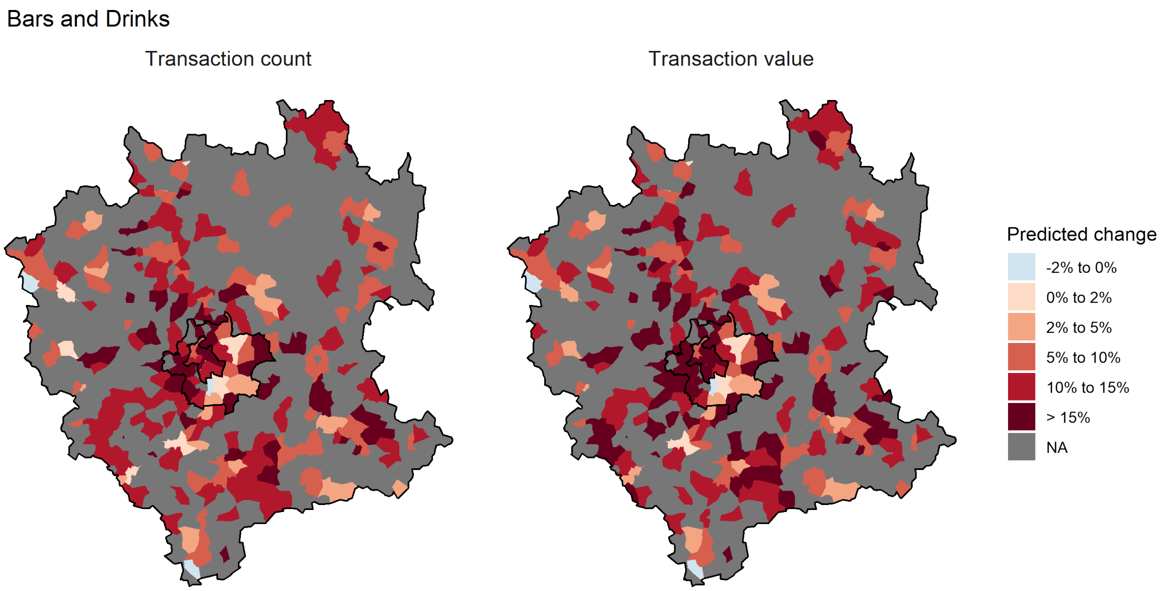
Note: The two figures show the effect of telework on transaction counts and transaction values, respectively, in the sector s = *Food Retail*. This is computed as the weekly average of the ratio $(\tilde{y}_{ids} - \tilde{y}^0_{ids})/\tilde{y}^0_{ids}$, where $\tilde{y}_{ids}$ denotes the model-predicted values, $\hat{y}_{ids}$, averaged over day $d \in$ {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 28: 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 29: 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 30: Effect of telework in Bars and Drinks

C.4.2 Significance of the aggregated results

Distribution of estimates over all iterations. Table 30 reports descriptive statistics of the computed variables across all iterations. Extreme values in the consumption substitution rate appear in the sectors Bars and Drinks and General Retail.[27]

Distribution of the net aggregated effect of telework. Table 31 shows that the only sector experiencing an aggregate telework effect significantly different from zero is the *Restaurants* sector, which experiences a net decline of 24% in consumer visits (proxied by transaction frequency) and a 20% decline in sales. Effects are also significant across all municipality groups, with effect sizes increasing with centrality: it is largest in the city of Lyon, followed by the rest of the urban core, the urban commuting zone, and rural municipalities. Figure 31 shows the empirical distribution of aggregate net effects of telework by sector and municipality group, and Figure 32 presents the empirical distribution of the aggregate net effect of telework by sector over the Lyon FUA as a whole.

Distribution of the average consumption substitution rate. Table 32 shows that the *Restaurant* sector exhibits a municipal consumption substitution rate significantly below unity. For one additional worker teleworking at home, only 36.4% (90% CI: [11.8%; 62.0%]) of restaurant spending is preserved relative to the presence of a worker at the workplace. Other sectors exhibit substitution rate non significantly different from unity.

Distribution of the net effect of telework by municipality. Table 33 reports the distribution of the average net effect of telework across municipalities, both for the full sample and for the subset with statistically significant estimates. For the latter, we provide separate descriptive statistics for significantly positive and significantly negative effects. In the *Restaurants* sector, 431 out of 460 (94%) municipalities with restaurant activity exhibit a statistically significant negative telework effect on transaction frequency, and 384 (83%) exhibit a statistically significant negative effect on transaction value. In the *Food Retail* sector, most municipalities with a statistically significant telework effect (16%–24% of all municipalities) benefit from telework, with larger growth rates observed for transaction value. In the *Bars and Drinks* sector, all municipalities with a statistically significant telework effect (8%-18% of all municipalities) benefit from telework, with similar growth rates observed between transaction frequency and value. In the *General Retail* sector, no significant telework effect is found.

Table 34 and Figure 33 reveal strong spatial heterogeneity in the sectoral impact of telework. In the *Restaurants* sector, the effect is significantly almost everywhere, and more negative in urban areas, consistent with reduced workplace-based consumption. By contrast, *Food Retail* and *Bars and Drinks* display more geographically diffuse effects, primarily within the commuting zone. Overall, these patterns suggest that telework induces a spatial reallocation of consumption, along with sectoral substitution, away from employment centers toward residential areas, rather than an overall significant decline in local spending.

[27] To limit the influence of such outliers, which arise from nonlinear transformations of estimated coefficient, we winsorize the bootstrap distributions within each municipality and report it in the tables' notes. Specifically, the lowest and highest X draws are replaced by the adjacent values, and mean estimates and confidence intervals are computed from the winsorized distributions.

Table 30: Descriptive statistics of estimates over all iterations, by sector

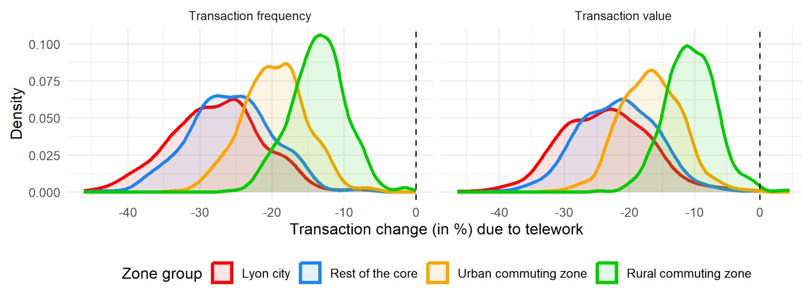
Variable	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	N
Panel A: Transaction frequency							
Panel A1: Restaurants							
CSR in pp	0.00	0.20	0.27	0.27	0.33	0.72	500
CSR in units	0.00	0.22	0.29	0.29	0.35	0.75	500
Δ_i%	-54.46	-19.16	-13.94	-14.44	-9.18	17.45	145,367
Δ_g%	-46.11	-26.98	-21.32	-21.65	-15.97	-0.96	2,000
Δ%	-41.80	-28.37	-24.44	-24.42	-20.78	-6.14	500
Panel A2: Food Retail							
CSR in pp	0.37	0.75	0.86	0.95	1.06	3.82	500
CSR in unit	0.36	0.81	0.95	1.05	1.15	4.66	500
Δ_i%	-16.56	-1.26	0.92	0.79	3.03	18.18	113,070
Δ_g%	-13.86	-2.54	-0.50	-0.42	1.71	14.30	2,000
Δ%	-10.64	-2.91	-1.02	-0.66	1.66	10.62	500
Panel A3: Bars and Drinks							
CSR in pp	0.02	0.98	1.41	3.68	2.28	487.66	500
CSR in units	0.02	1.08	1.55	4.07	2.51	516.67	500
Δ_i%	-46.39	3.63	11.09	12.32	19.60	128.34	68,641
Δ_g%	-42.23	3.37	12.09	13.64	21.66	105.43	2,000
Δ%	-35.37	3.22	14.14	15.49	25.38	87.93	500
Panel A4: General Retail							
CSR in pp	0.02	0.54	0.77	1.88	1.06	482.04	500
CSR in units	0.02	0.61	0.88	2.12	1.19	540.14	500
Δ_i%	-21.95	-3.31	-0.53	-0.63	1.99	31.89	83,755
Δ_g%	-18.72	-4.67	-1.43	-1.70	1.15	19.67	2,000
Δ%	-15.11	-5.17	-1.75	-2.02	0.98	14.54	500
Panel B: Transaction value							
Panel B1: Restaurants							
CSR in pp	0.00	0.25	0.34	0.34	0.42	0.94	500
CSR in units	0.00	0.27	0.36	0.36	0.44	0.99	500
Δ_i%	-56.36	-16.45	-11.37	-11.84	-6.76	23.04	145,367
Δ_g%	-46.44	-23.29	-17.67	-18.19	-12.61	4.56	2,000
Δ%	-40.40	-24.52	-20.45	-20.34	-16.19	0.43	500
Panel B2: Food Retail							
CSR in pp	0.41	0.92	1.23	2.03	1.88	53.60	500
CSR in units	0.40	1.01	1.33	2.23	2.06	54.91	500
Δ_i%	-19.92	1.20	4.47	4.56	7.77	53.43	113,070
Δ_g%	-14.49	0.34	3.78	4.30	7.90	44.31	2,000
Δ%	-10.57	-0.12	3.57	3.96	7.92	30.11	500
Panel B3: Bars and Drinks							
CSR in pp	0.10	1.03	1.44	10.78	2.40	3264.67	500
CSR in units	0.12	1.15	1.62	13.10	2.60	4187.47	500
Δ_i%	-38.90	4.72	12.64	14.13	21.87	134.45	68,641
Δ_g%	-28.68	4.90	13.84	15.85	24.60	106.17	2,000
Δ%	-22.25	4.89	15.44	17.44	28.39	79.29	500
Panel B4: General Retail							
CSR in pp	0.00	0.29	0.53	0.98	0.85	34.14	500
CSR in units	0.00	0.33	0.60	1.10	0.98	38.24	500
Δ_i%	-27.33	-6.04	-3.19	-3.30	-0.46	24.81	83,755
Δ_g%	-24.29	-7.86	-4.43	-4.64	-1.39	17.51	2,000
Δ%	-18.69	-8.03	-4.89	-4.89	-1.79	11.53	500

Note: For sectors experiencing statistically significant telework-induced demand shocks, the table reports the bootstrap distribution (500 iterations) of the estimated consumption substitution rates—expressed both in percentage points of workers and in teleworker levels—together with the estimated net telework effect (in percent) at the municipality, municipality-group, and Lyon FUA levels.

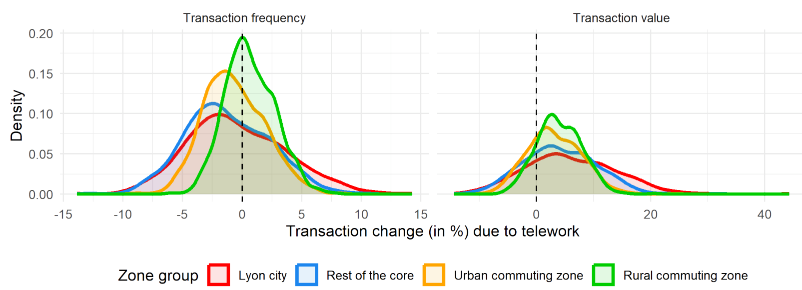
Table 31: Bootstrap aggregated effects of telework by sector (% change in transactions)

	Mean	90% CI
Panel A: Transaction frequency		
Panel A1: Restaurants		
Lyon city	-27.631	[-38.125; -17.348]
Rest of the core	-25.637	[-35.040; -16.345]
Urban commuting zone	-19.677	[-27.048; -12.438]
Rural commuting zone	-13.638	[-20.289; -7.452]
All FUA	-24.417	[-33.999; -15.388]
Panel A2: Food Retail		
Lyon city	-0.437	[-6.897; 6.570]
Rest of the core	-1.224	[-6.718; 4.755]
Urban commuting zone	-0.673	[-4.578; 3.676]
Rural commuting zone	0.653	[-2.634; 4.372]
All FUA	-0.661	[-5.652; 4.789]
Panel A3: Bars and Drinks		
Lyon city	19.093	[-12.309; 60.055]
Rest of the core	13.374	[-12.731; 44.895]
Urban commuting zone	9.337	[-8.343; 30.612]
Rural commuting zone	12.757	[-2.944; 31.06]
All FUA	15.494	[-10.033; 47.403]
Panel A4: General Retail		
Lyon city	-1.692	[-11.799; 8.875]
Rest of the core	-2.829	[-11.293; 5.568]
Urban commuting zone	-1.952	[-8.315; 4.547]
Rural commuting zone	-0.343	[-5.511; 5.062]
All FUA	-2.021	[-9.602; 5.918]
Panel B: Transaction value		
Panel B1: Restaurants		
Lyon city	-23.693	[-33.98; -12.894]
Rest of the core	-21.735	[-30.952; -12.435]
Urban commuting zone	-16.715	[-23.744; -9.424]
Rural commuting zone	-10.598	[-16.88; -4.296]
All FUA	-20.340	[-29.168; -11.237]
Panel B2: Food Retail		
Lyon city	5.967	[-6.221; 18.720]
Rest of the core	4.084	[-5.876; 14.418]
Urban commuting zone	3.160	[-4.117; 10.765]
Rural commuting zone	3.971	[-2.304; 10.481]
All FUA	3.961	[-4.836; 12.770]
Panel B3: Bars and Drinks		
Lyon city	22.226	[-11.774; 63.770]
Rest of the core	15.510	[-11.227; 47.891]
Urban commuting zone	11.233	[-7.853; 32.723]
Rural commuting zone	14.428	[-2.149; 33.897]
All FUA	17.438	[-9.192; 49.384]
Panel B4: General Retail		
Lyon city	-5.862	[-16.442; 4.358]
Rest of the core	-5.700	[-13.977; 2.814]
Urban commuting zone	-4.249	[-10.486; 2.170]
Rural commuting zone	-2.746	[-8.686; 2.523]
All FUA	-4.895	[-12.628; 2.845]

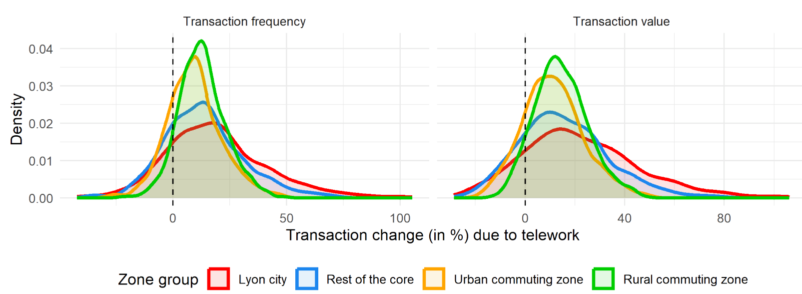
Note: For sectors experiencing statistically significant telework-induced demand shocks, the table reports the bootstrap aggregated average effect of telework on transaction frequency and value, computed over 500 iterations. Results are shown by municipality group and for the entire Lyon FUA, together with their 90% confidence intervals.



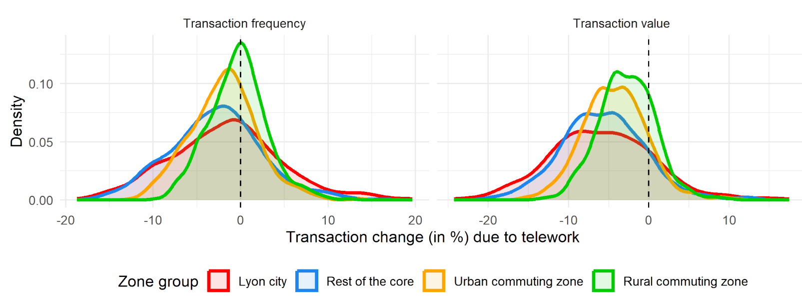
(a) Restaurants



(b) Food Retail



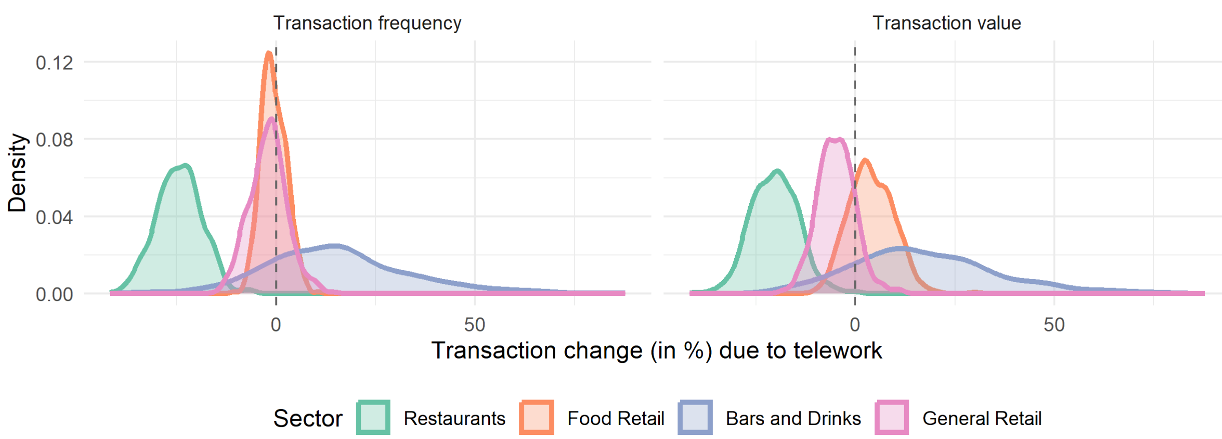
(c) Bars and Drinks



(d) General Retail

Note: The Figures display the bootstrap distribution (500 iterations) of the estimated net telework effects (in percent) on transaction frequency [1ex] and value within each municipality-group for the sector of Restaurants (subfigure A), Food Retail (subfigure B), Bars and Drinks (subfigure C), and General Retail (subfigure D).

Figure 31: Bootstrap distribution of the average daily aggregated effect of telework, by municipalities' group and sector



Note: The Figures display the bootstrap distribution (500 iterations) of the estimated net telework effects (in percent) on transaction frequency and value over the entire Lyon FUA, for each sector experiencing significant telework-inducde demand shocks.

Figure 32: Bootstrap distribution of the average daily aggregated effect of telework, by sector

Table 32: Consumption substitution rates by sector

	Mean	90% CI
Panel A: Transaction frequency		
Panel A1: Restaurants		
percentage points	0.268	[0.084; 0.441]
units	0.287	[0.093; 0.470]
Panel A2: Food Retail		
percentage points	0.953	[0.605; 1.560]
units	1.046	[0.654; 1.736]
Panel A3: Bars and Drinks		
percentage points	3.685	[0.538; 7.188]
units	4.066	[0.616; 8.437]
Panel A4: General Retail		
percentage points	1.875	[0.173; 2.182]
units	2.115	[0.200; 2.451]
Panel B: Transaction value		
Panel B1: Restaurants		
percentage points	0.340	[0.107; 0.575]
units	0.364	[0.118; 0.620]
Panel B2: Food Retail		
percentage points	2.032	[0.67; 5.237]
units	2.233	[0.721; 5.994]
Panel B3: Bars and Drinks		
percentage points	10.778	[0.632; 10.862]
units	13.097	[0.717; 11.898]
Panel B4: General Retail		
percentage points	0.977	[0.046; 2.825]
units	1.103	[0.053; 3.326]

Note: For sectors experiencing statistically significant telework-induced demand shocks, the table reports the bootstrap average work-to-home consumption substitution rates (for both transaction count and value), expressed both in percentage points of workers and in teleworker levels, computed over 500 iterations, along with their 90% confidence intervals.

Table 33: Distribution of municipalities' average telework effect by sector (All vs Significant)

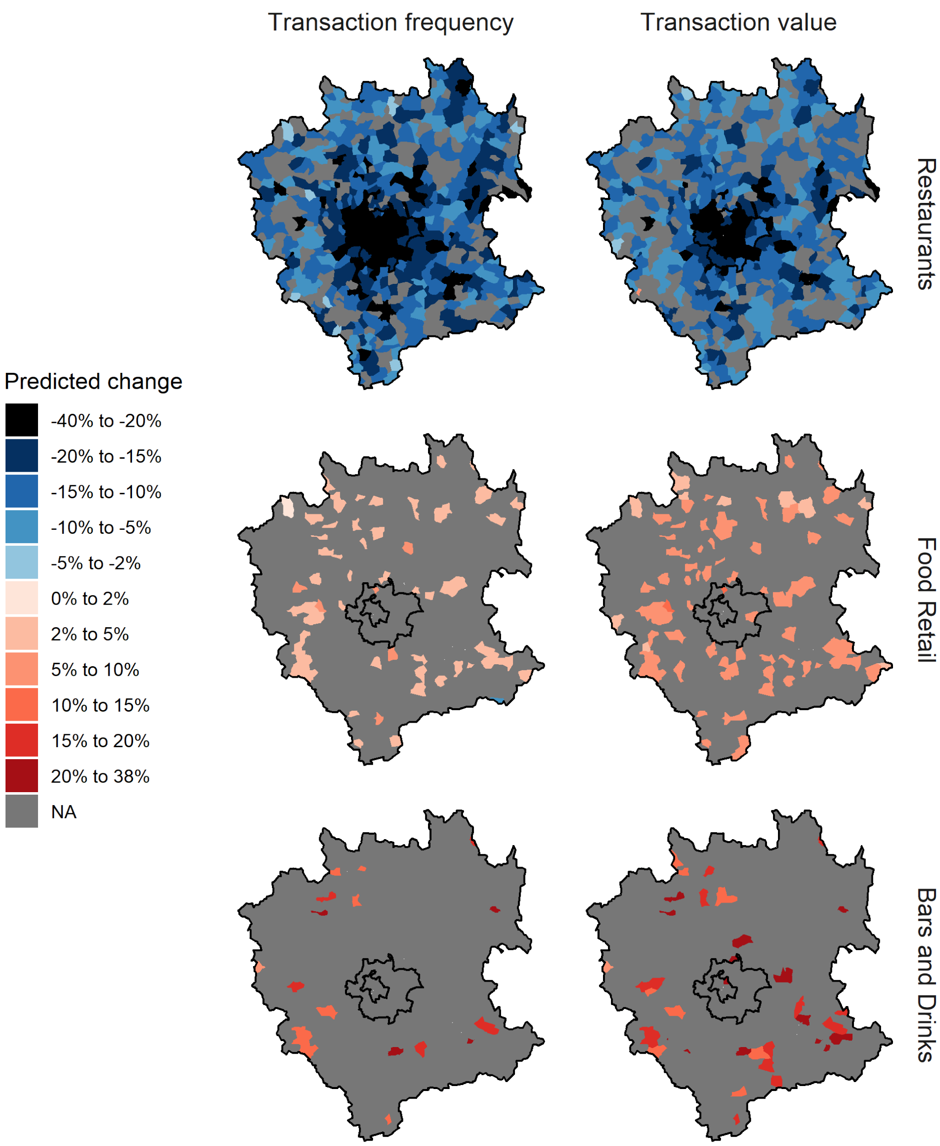
Sample	Min	Q1	Median	Q3	Max	N
Panel A: Transaction frequency						
Panel A1: Restaurants						
All	-39.854	-18.266	-14.431	-10.403	4.904	460
Significant positive	-	-	-	-	-	0
Significant negative	-39.854	-18.478	-14.846	-11.182	-3.405	431
Panel A2: Food Retail						
All	-7.935	-0.673	1.007	2.238	7.199	357
Significant positive	1.859	3.256	3.814	4.307	7.199	57
Significant negative	-7.935	-7.935	-7.935	-7.935	-7.935	1
Panel A3: Bars and Drinks						
All	0.388	8.497	12.531	15.321	32.730	217
Significant positive	8.545	13.443	15.321	20.000	23.017	17
Significant negative	-	-	-	-	-	0
Panel A4: General Retail						
All	-5.769	-1.682	-0.413	0.473	4.500	265
Significant positive	-	-	-	-	-	0
Significant negative	-	-	-	-	-	0
Panel B: Transaction value						
Panel A1: Restaurants						
All	-36.702	-15.493	-11.780	-8.020	7.146	460
Significant positive	7.146	7.146	7.146	7.146	7.146	1
Significant negative	-36.702	-16.464	-12.995	-10.017	-4.614	383
Panel A2: Food Retail						
All	-4.683	2.788	4.831	6.417	13.787	357
Significant positive	3.239	5.710	6.918	7.936	13.787	85
Significant negative	-	-	-	-	-	0
Panel A3: Bars and Drinks						
All	0.778	9.764	14.489	17.469	37.085	217
Significant positive	9.488	15.124	17.677	22.013	37.085	38
Significant negative	-	-	-	-	-	0
Panel A4: General Retail						
All	-7.931	-4.197	-3.081	-2.352	0.993	265
Significant positive	-	-	-	-	-	0
Significant negative	-5.031	-5.031	-5.031	-5.031	-5.031	1

Note: The table reports the bootstrap distribution of average telework effects across municipalities by sector. Panel A refers to transaction frequency, while Panel B refers to transaction value. For each panel, ”Significant positive” and ”Significant negative” indicate the subset of municipalities where the effect is statistically significant at the 10% level and positive or negative, respectively.

Table 34: Distribution of municipalities with significant average telework effect, by sector

	Transaction frequency			Transaction value		
		Significant			Significant	
	All	> 0	< 0	All	> 0	< 0
Panel A: Restaurants						
Lyon city	9	0	9	9	0	9
	(100%)	(0%)	(100%)	(100%)	(0%)	(100%)
Rest of the core	30	0	30	29	0	29
	(100%)	(0%)	(100%)	(96.7%)	(0%)	(96.7%)
Urban commuting zone	143	0	143	138	0	138
	(99.3%)	(0%)	(99.3%)	(95.8%)	(0%)	(95.8%)
Rural commuting zone	249	0	249	208	1	207
	(89.9%)	(0%)	(89.9%)	(75.1%)	(0.4%)	(74.7%)
Panel B: Food Retail						
Lyon city	0	0	0	0	0	0
	(0%)	(0%)	(0%)	(0%)	(0%)	(0%)
Rest of the core	1	1	0	2	2	0
	(3.3%)	(3.3%)	(0%)	(6.7%)	(6.7%)	(0%)
Urban commuting zone	9	9	0	18	18	0
	(6.5%)	(6.5%)	(0%)	(12.9%)	(12.9%)	(0%)
Rural commuting zone	48	47	1	65	65	0
	(26.8%)	(26.3%)	(0.6%)	(36.3%)	(36.3%)	(0%)
Panel C: Bars and Drinks						
Lyon city	0	0	0	1	1	0
	(0%)	(0%)	(0%)	(11.1%)	(11.1%)	(0%)
Rest of the core	0	0	0	0	0	0
	(0%)	(0%)	(0%)	(0%)	(0%)	(0%)
Urban commuting zone	2	2	0	6	6	0
	(2.2%)	(2.2%)	(0%)	(6.5%)	(6.5%)	(0%)
Rural commuting zone	15	15	0	31	31	0
	(16.3%)	(16.3%)	(0%)	(33.7%)	(33.7%)	(0%)

Note: The table reports the number of municipalities exhibiting a statistically significant average telework effect by zone group and sector (at least at the 10% significance level). Columns "All", "> 0", and "< 0" respectively indicate the total number of municipalities with a significant telework effect, those with a significant positive effect, and those with a significant negative effect. Panel A refers to the Restaurant sector, Panel B to Food Retail, Panel C to Bars and Drinks. Percentages reported in parentheses are computed relative to the total number of municipalities within each zone group.



Note: The maps show municipalities with statistically significant average telework effects on transaction frequency (left panel) and transaction value (right panel) for each of the sector experiencing significant telework effects (Restaurants are shown in the top panel, Food Retail in the middle panel, and Bars & Drinks in the bottom panel). Only municipalities with significant effects at the 10% level are colored, with positive and negative effects distinguished by the color scale. Municipalities shown in grey exhibit non-significant effects.

Figure 33: Statistically significant telework effect on transaction frequency and value 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 35, incorporates both direct telework effects within municipalities and indirect effects from neighboring areas, allowing us to capture the complex spatial interdependencies in consumption patterns.

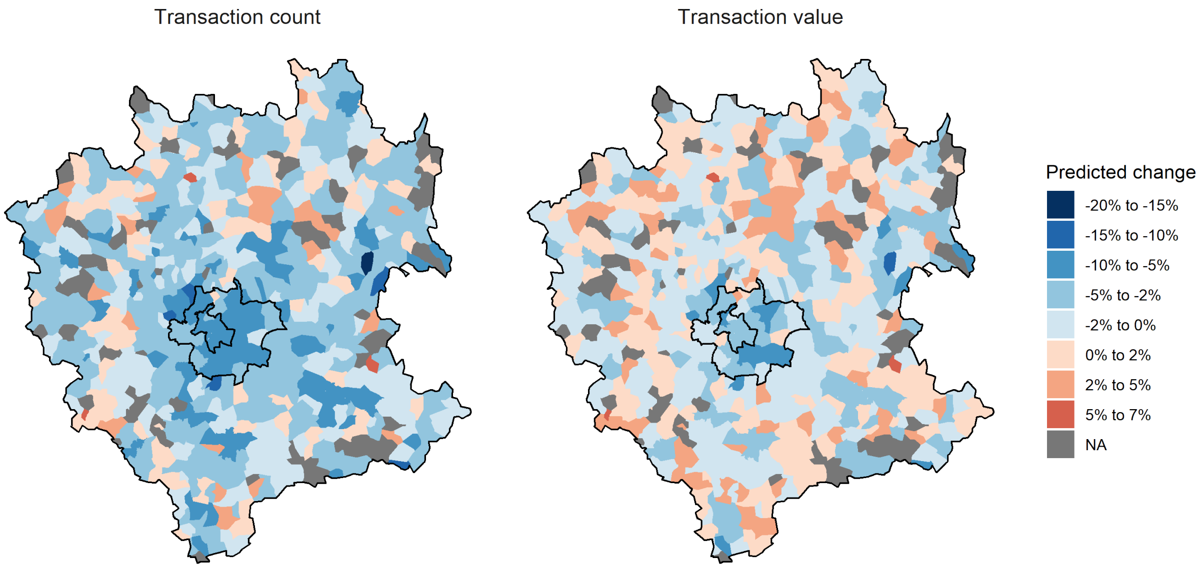
Figure 34 visualizes the average daily effects of telework on both transaction counts and values, incorporating spatial spillovers from neighboring municipalities. This aggregate analysis reveals that while telework generates net negative effects across most zone groups, the magnitude varies significantly, with Lyon city experiencing an 8.08% reduction in transactions and rural commuting zones showing a much smaller 2.05% decline.

Table 36 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.

Table 35: Spatial spillovers, heterogeneity by zone group

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



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 $d \in \{\text{Mon; Tue; Wed; Thu; Fri}\}$, 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 34: Average daily effect of telework (spatial spillover model)

Table 36: Aggregate Impact of Telework: Predicted Percentage Change in Transactions by Spatial Zone

		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.

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 enables us to estimate teleworking patterns for each municipality and day of the week, closely reflecting actual observed behavior.

We develop a method to estimate the daily 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:

$$\text{Residents}_{it} = \widehat{\alpha}_i \times \text{Inactives}_i + \sum_k \gamma_{gkt} \times \text{Part-time workers}_{ik} + \widehat{\beta_{it}} \times \text{Teleworkers}_i \qquad (14)$$

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 constant daily share of inactive residents and the varying 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 daily telework shares at home ($\text{WFH}_{it}^{(\mathcal{H})}$) and workplace ($\text{WFH}^{(\mathcal{W})}$) 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 35 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 36 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

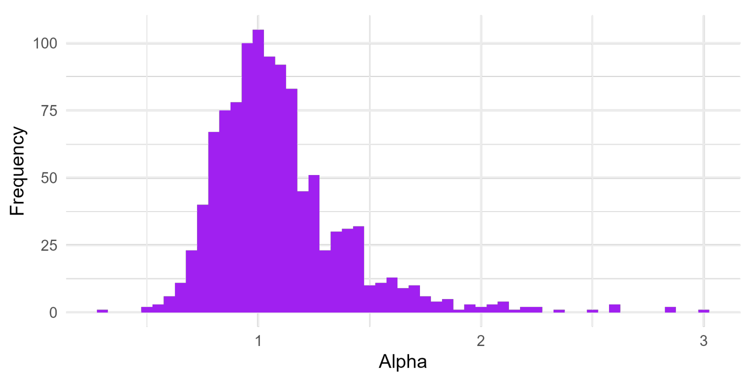
$$\beta_{it}^{norm} = \frac{\beta_{it} - \min_d \beta_{id}}{\max_d \beta_{id} - \min_d \beta_{id}} \tag{15}$$

2. Sum correction

$$\delta_i = 2.428 - \sum_{t=1}^{n_i} \beta_{it}^{norm} \tag{16}$$

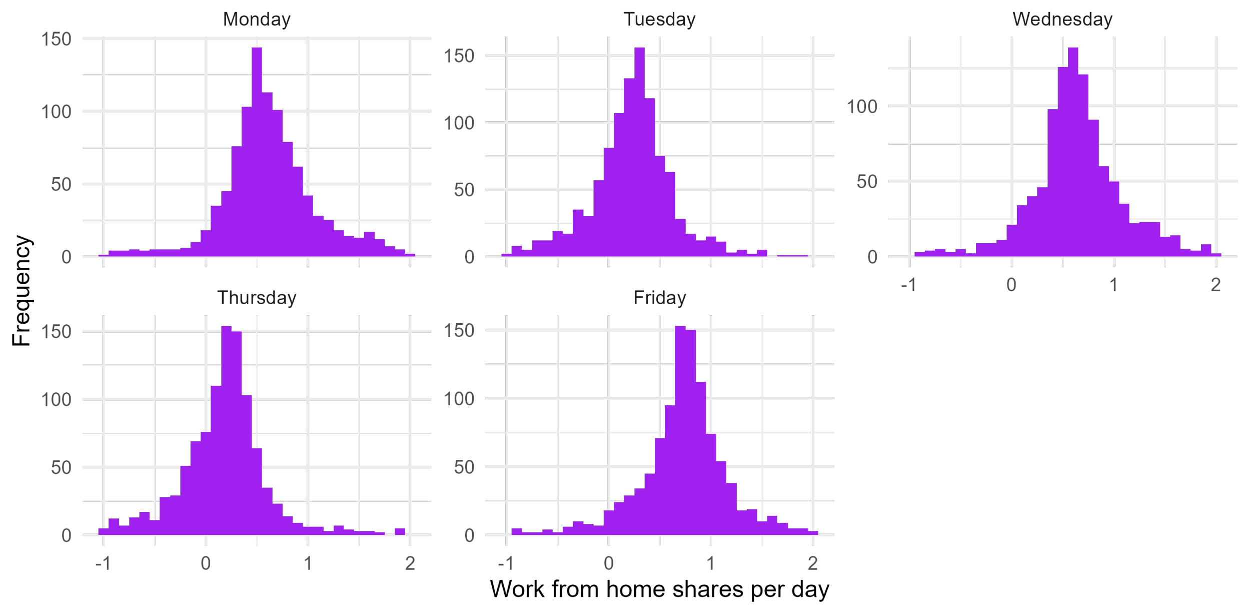
$$\beta_i^{scaled} = \begin{cases} \beta_i^{norm} + \frac{\delta_i}{n_i - 2} & \text{if } \beta_i^{norm} \in (0;1) \\ \beta_i^{norm} & \text{otherwise} \end{cases} \tag{17}$$

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.



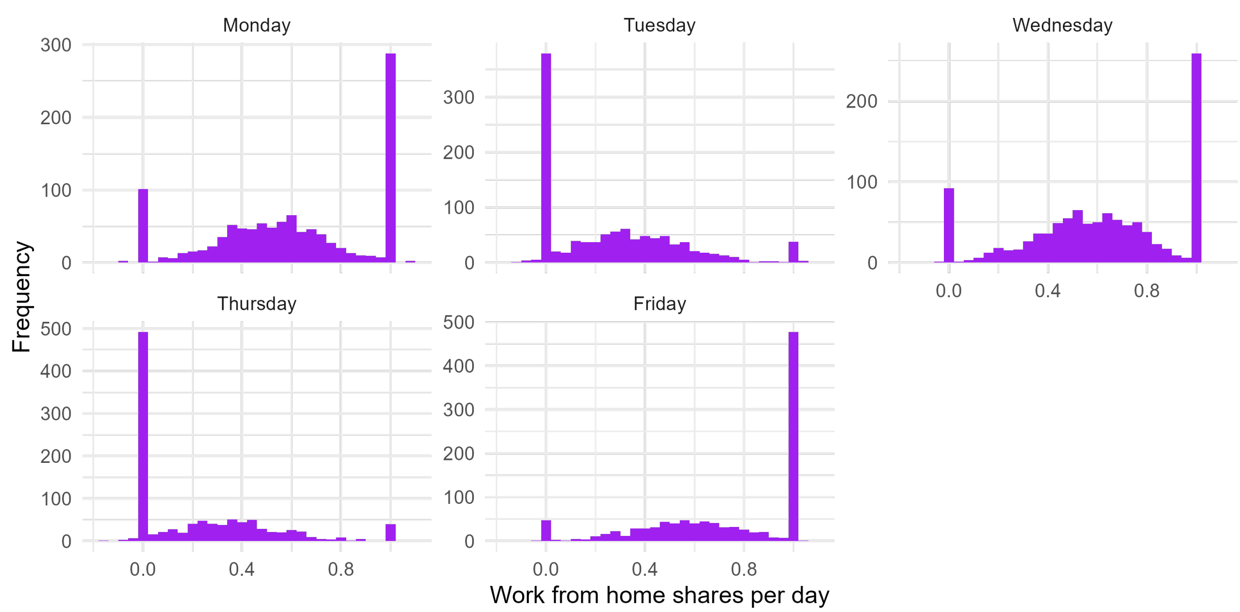
Note: The figure shows the distribution of the computed share of inactive residents supposed to be in their residence zone during working hours on weekdays.

Figure 35: Alpha



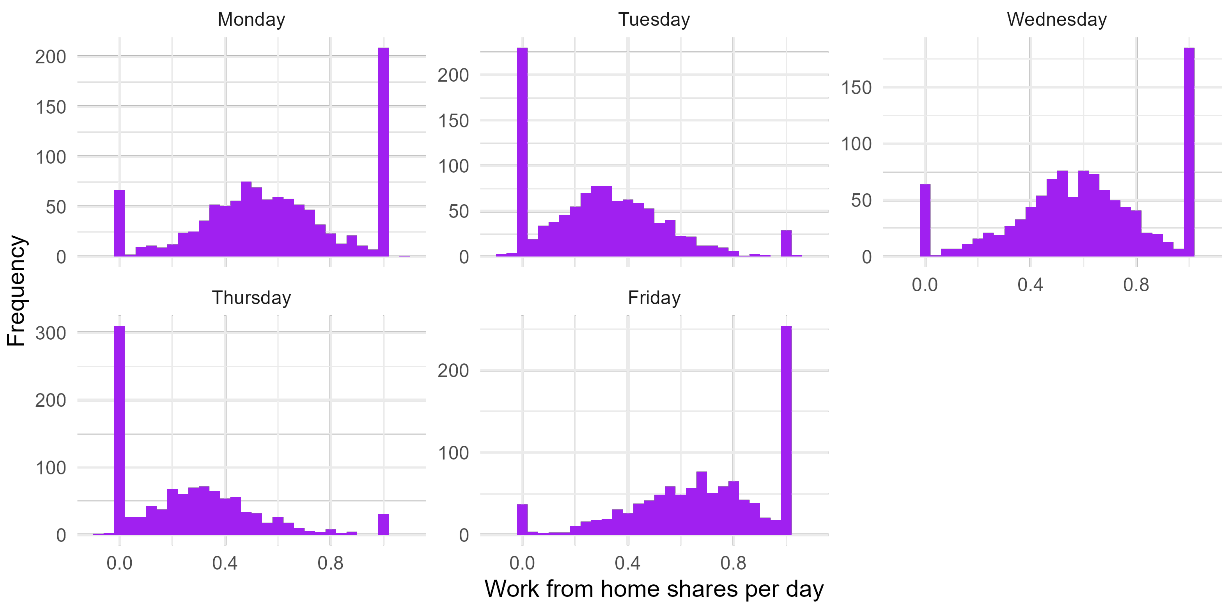
Note: The figure shows the distribution of the computed share of resident teleworkers supposed to be in their residence zone (working from home) during working hours on each weekday.

Figure 36: 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 37: 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 38: Scaled Beta$^{(2)}$ (on selected observations - those with Beta out of the bound [0;1])