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

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September 18, 2026

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 opposing 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

*This research was supported by the ANR MobiTIC project (grant number ANR-19-CE22-0010), a collaborative initiative between Orange, Université Gustave Eiffel, and INSEE, and by the Research Chair Digital Finance under the aegis of the Risk Foundation, a joint initiative by Groupement des Cartes Bancaires CB, Telecom Paris and University Paris-Panthéon-Assas. The findings and interpretations expressed herein are solely those of the authors and do not reflect the positions of the affiliated institutions. We would like to thank John Galbraith who meticulously followed our progress on this project and continuously enriched our discussions; Michael Stops and Immanuel Feld for their rigorous discussions of our paper at the 14th European Meeting of the Urban Economics Association and the 2026 University of Reading Workshop in Urban Economics and Economic Geography; Corinne Prost, Romain Lesur and Mélina Hillion for their thorough review; Loÿs Moulin, Cédric Le Quilliec, Katérina Levallois, and Samuel Willy for their helpful comments on earlier versions of the manuscript. We are grateful for the feedback and questions received from participants at seminars and conferences, including the University of Reading Workshop in Urban Economics and Economic Geography, the 15th European Meeting of the UEA, LEMNA Young Researchers' Day, the GAINS seminar, the 2026 ADRES Job Market Conference, the MNO-MINDS Final Conference (Eurostat CROS), the 11th AFREN Digital Economics Conference, the 2025 Télécom Paris Research Retreat, the 73rd Congress of the AFSE, and the 14th European Meeting of the UEA.

†This research was conducted while the author was affiliated with Université Gustave Eiffel, Télécom Paris and Insee. The author is currently affiliated with Nantes Université. Contact: gabrielle.gambuli@gmail.com

1 Introduction

The COVID-19 pandemic accelerated the adoption of hybrid work,[1] where employees split their time between home and office. In France, the share of workers teleworking at least one day per week[2] surged from 3% in 2017 to 20% in 2024, with teleworkers now averaging two to three days working from home (Enquête Emploi, INSEE).[3], for annual telework statistics. 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 this municipality-day panel, our identification strategy combines two key elements. First, we separately measure the two opposing demand shocks generated by telework:

[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 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 Online Appendix B.1, Table OA.4

increased worker presence at home and reduced presence at their official workplace. This distinction is central, as observing both margins simultaneously allows us to capture the full spatial reallocation of consumption induced by telework and to recover its aggregate net effect. Second, we exploit differential exposure to aggregate daily fluctuations in telework intensity across municipalities. We construct a measure of municipalities' structural exposure to telework based on the residential–workplace composition of workers by occupation and urban group, using labor force survey and census data, and interact it with a common daily telework intensity estimated from mobile phone records. Conditional on key confounders and fixed effects, identification comes from cross-municipality differences in exposure to common telework shocks, which are plausibly orthogonal to residual local demand shocks. This framework allows us to estimate the effect of telework on local consumption and its net impact on aggregate weekday spending within the 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 telework-related jobs remain highly concentrated in the urban core (around 70% of teleworkers are employed there), while residential locations are more spatially dispersed (60% reside in the core), suggesting a spatial redistribution of spending from the urban core toward suburban areas. Moreover, substantial cross-municipality commuting flows exist both within the urban core and within the suburbs, further reshaping the geography of consumption, as illustrated by the spatial imbalance index in Figure 1.

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 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 common to municipalities of similar urban contexts, while observable confounders are explicitly accounted for, such as the presence of part-time workers, weather, and public transport disruption. Together, these design features support a causal interpretation of the estimated effects, and allow 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. To reinforce this identification strategy, we complement our baseline specification with a shift-share instrumental variable (IV) approach, implemented via a two-stage residual inclusion (2SRI) procedure suited to our nonlinear PPML setting. The instruments exploit exogenous variation in pre-pandemic occupational telework potential and daily deviations in stay-at-home patterns relative to a comparison group of part-time executives.

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 is consistent with spending being nearly fully reallocated from workplace to home, leaving aggregate consumption unchanged, though we cannot rule out incomplete substitution in transaction value. 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 and statistically significant declines in central and more urbanized areas: -6.8% in Lyon city, -6.7% in the rest of the urban core, and -4.8% in the urban commuting zone; the decline in rural municipalities (-2.7%) is smaller and not statistically distinguishable from zero. 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. 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 suggestive evidence against a purely reverse-causal interpretation. Telework significantly affects sectors whose weekly spending pattern does not naturally track telework's own weekly rhythm—restaurants and bars, for instance, see activity rise gradually across the week rather than spiking on Wednesdays and Fridays as telework does—while showing no effect in sectors whose weekly pattern already mirrors this Wednesday-Friday peak (e.g., general retail). This asymmetry is difficult to reconcile with a story in which consumption needs alone drive telework choices, which would plausibly affect spending across sectors more uniformly.

To ensure the robustness of our findings, we conduct a series of additional tests, all documented in Appendix C, complementing the shift-share IV approach introduced above. These tests address potential econometric concerns through two further 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.

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. Our findings indicate no robust evidence of intertemporal consumption substitution between weekdays and weekends, reinforcing the credibility of our baseline estimates. Specifically, municipalities with a higher concentration of resident teleworkers do not exhibit systematically higher or lower consumption activity on weekdays relative to weekends compared to municipalities with a lower concentration of teleworkers. Instead, we observe a spatial reallocation of spending associated with telework. The higher the concentration of resident teleworkers, the more weekday spending shifts toward residential areas, while weekend consumption moves in the opposite direction, away from residential areas and toward non-residential locations. Together, these findings suggest that telework mainly impacts the spatial distribution of consumption by redirecting demand across locations, with a relative increase in residential-area transactions during weekdays and in non-residential-area transactions during weekends, while there is no robust evidence of systematic intertemporal substitution between weekdays and weekends in either transaction counts or volumes. 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. Beyond estimating this net effect, jointly modeling both margins allows us to characterize where and in which sectors the underlying reallocation of spending occurs—identifying which municipalities and business types gain or lose from telework's spatial and sectoral reshuffling of demand—a dimension that a net-effect estimate alone, or an analysis of only one margin, cannot reveal.

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 effect 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 new empirical evidence that substitution between home- and workplace-based consumption is incomplete, particularly in terms of transaction frequency.

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) documents 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 presents the empirical strategy and the main results on the impact of telework on local consumption. Section 5 extends the analysis to spatial spillovers and intertemporal substitution. Section 6 concludes. Additional derivations, robustness checks, and data details are reported in the Appendix; supplementary results, referenced throughout as "Online Appendix," are provided in a separate Online Appendix available alongside the paper.

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. A 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 5a, 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 Online Appendix A.1, 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).

[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.

Labor Force Survey. To estimate telework and part-time work patterns, we use data from the *Enquête Emploi* (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 regional telework averages are then applied to the census residence-workplace-occupation matrix. Specifically, each worker's municipality of residence and occupation determines the expected number of teleworkers by municipality of residence and by workplace. This projection forms the basis of our daily telework estimation. Similarly, the EEC provides data to compute national daily averages of the share of part-time workers who are typically off work from Monday to Friday, by occupation and residential location type within FUAs. These shares are applied to the number of part-time workers in each census cell to estimate, for each day of the 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 business sector (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 business sector, municipality, and day in September 2022. For municipality $\times$ date $\times$ sector combinations not observed in the data,

[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.

[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).

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 Online Appendix A.2, Figure OA.1).

3 Measuring Spatial and Temporal Patterns of Telework

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

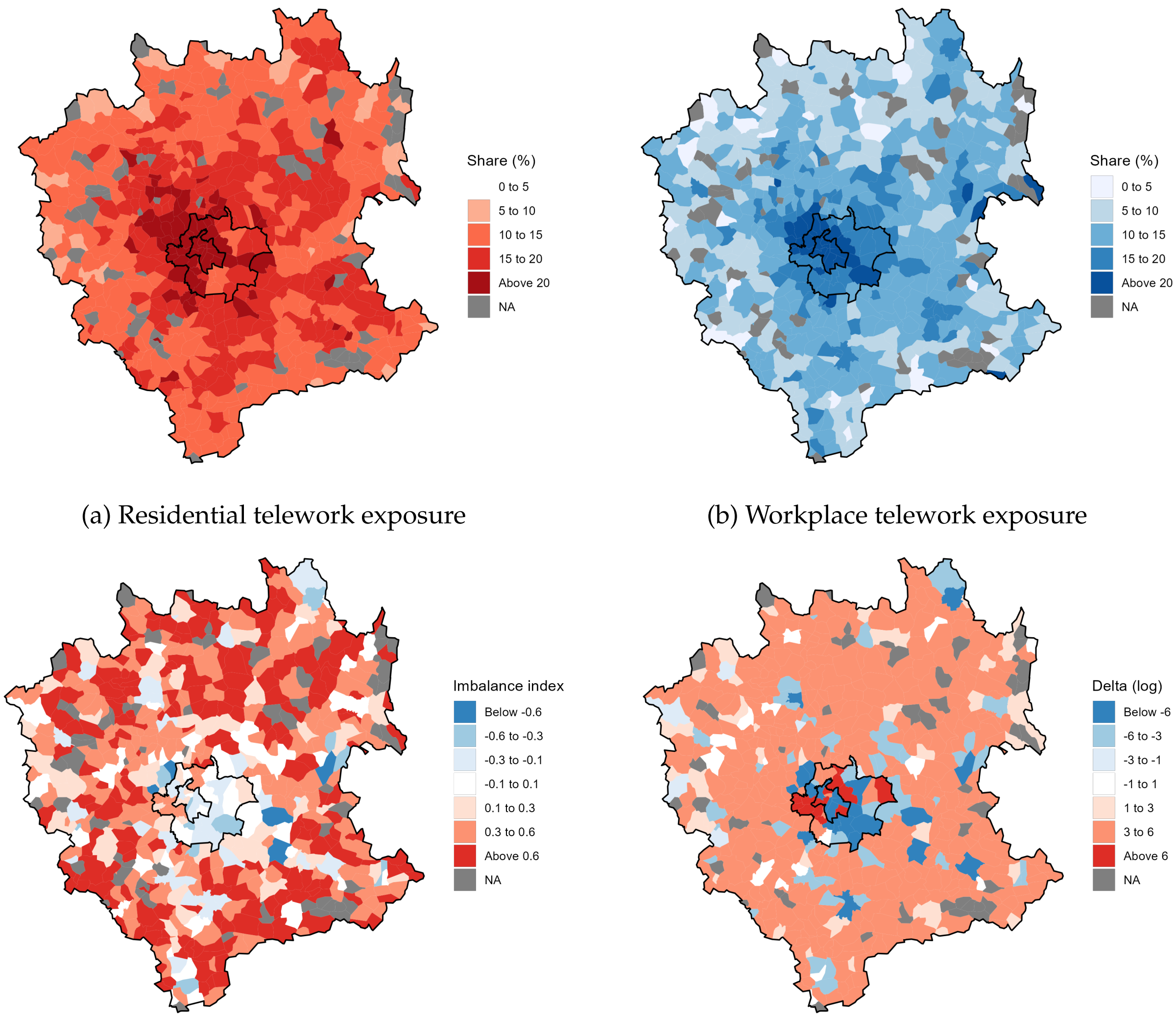
3.1 Geography of Teleworkers' Residence and Workplace

We estimate the potential for telework across the Lyon FUA by combining labor force survey data and population census for workers distributions across their residence and workplace. Using the French Labor Force Survey (EEC, Q4 2022), we compute the share of teleworkers, $\tau_{g(i)k}$, 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 Figure 6 in Appendix B. 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.



(a) Residential telework exposure

(b) Workplace telework exposure

(c) Relative residential-employment imbalance

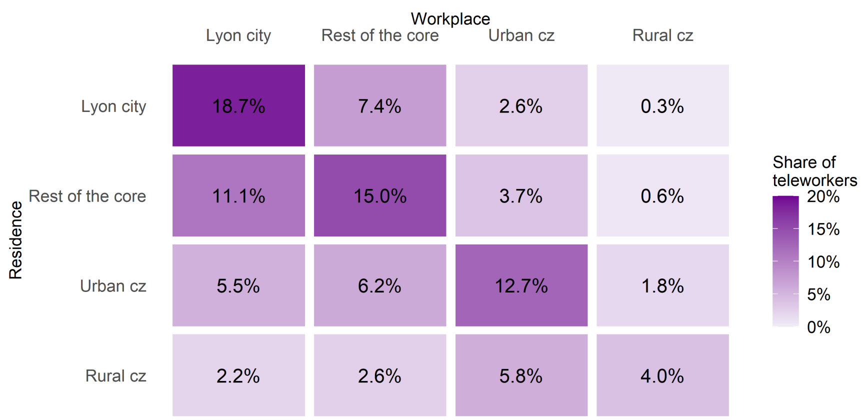
(d) Absolute residential-employment imbalance

Note: Panel (a) shows the municipality-level share of employed residents who may be present at home when teleworking ($\mathrm{TE}_i^{(\mathcal{H})}$). Panel (b) displays the share of workers who may be absent from their workplace when teleworking ($\mathrm{TE}_i^{(\mathcal{W})}$). Panel (c) presents the imbalance between teleworkers' residential and employment locations using the normalized index $\frac{\text{Teleworkers}_i^{(\mathcal{H})} - \text{Teleworkers}_i^{(\mathcal{W})}}{\text{Teleworkers}_i^{(\mathcal{H})} + \text{Teleworkers}_i^{(\mathcal{W})}}$. Positive values indicate municipalities hosting proportionally more teleworking residents than teleworking jobs, whereas negative values indicate employment centers that attract more teleworkers than they host as residents. Panel (d) maps the signed logarithmic transformation of the difference between resident teleworkers and workplace-based teleworkers, defined as $\text{sign}(x)\log(1 + |x|)$, where $x = \text{Teleworkers}_i^{(\mathcal{H})} - \text{Teleworkers}_i^{(\mathcal{W})}$.

Figure 1: Spatial distribution of teleworkers and telework residential-employment imbalance

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

These differences between residential and workplace locations imply substantial spatial mobility among teleworkers, which we characterize through commuting patterns. Most potential teleworkers (80.1%) reside and work in different municipalities: 19.9% work in the same municipality, 12.0% commute to an adjacent municipality, and 68.1% to a non-adjacent municipality. This spatial separation provides the variation needed to distinguish between home- and workplace-based consumption in our identification strategy. Commuting distances are also substantial, with a median of 9.3 km (mean: 32.8 km; p90: 55.1 km; p95: 110 km), and a long right tail driven by a minority of long-distance commuters. Figure 2 illustrates the spatial distribution of these commutes across four spatial groups defined by density and location within the FUA: Lyon city, the rest of the core, the urban commuting zone, and the rural commuting zone. While 50.4% of teleworkers reside and work within the same group, the prevalence of inter-municipality commuting points to substantial spatial reallocation within groups. At the same time, 33.4% commute from lower- to higher-density groups, indicating substantial reallocation across groups as well. Together, these patterns suggest that telework may redistribute consumption both within and across the spatial groups that structure our analysis.



Note: The figure shows the joint distribution of potential teleworkers' residence and workplace across the four spatial groups of the Lyon Functional Urban Area (FUA): Lyon city, the rest of the core, the urban commuting zone, and the rural commuting zone. We estimate approximately 220,000 potential teleworkers in the Lyon FUA, corresponding to about 19% of the working population.

Figure 2: Teleworkers' commuting matrix across spatial groups

3.2 Daily Rhythms of Telework: When People Work from Home

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

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

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

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 Online Appendix B.2, Figure OA.3. 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 (assumed constant across days). 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] Together, these checks confirm the reliability of our results.

[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) same-Iris workers in the census. Since workplace information is only available at the municipality level, residents working within their Iris of residence contribute to the observed presence rate, leading to an upward bias in $\widehat{\alpha}$.

[11] Online Appendix B.3, Table OA.5, 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.2) shows close alignment with our estimates. This external validation also speaks to the concern that residential presence during working hours might reflect activities other than telework—such as shopping, dining, or running errands—rather than actual telework: because our day-of-week estimates closely track independently measured office attendance, they are unlikely to be driven by such alternative activities, which would not be expected to follow the same systematic weekly pattern.

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

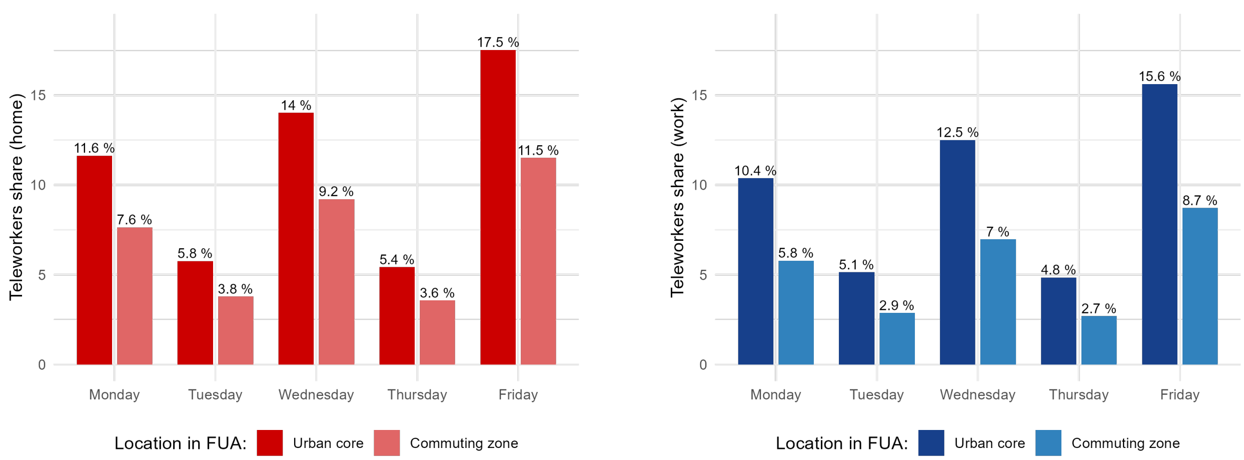
Note: Signif. codes: ***: 0.01, **: 0.05, *: 0.1, +: 0.15, -:0.2. Clustered standard-errors at the Iris zone level in parentheses. The reference number of teleworked days (conditional on teleworking) reported in the table, used to validate our results, is calculated from the Q4 2022 Labor Force Survey (*Enquête Emploi*) 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 core municipalities are estimated to work remotely 3.4 days per week on average, compared to 2.5 days in the commuting zone.[12]

[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

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. We also explore finer-grained Iris-level estimation methods, detailed in Online Appendix G, which yield qualitatively consistent results (see Online Appendix C.6, Table OA.10).

Figure 3 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.



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

the regional benchmark.

4 The Impact of Telework on Daily Spending

This section investigates the 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. 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.

4.1 Empirical Framework

4.1.1 Baseline PPML Model

To identify the effects of telework on in-store spending, our strategy exploits the systematic within-municipality variation in telework practice 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-by-urban-group fixed effects capture spending patterns that vary over time but are common to municipalities sharing a similar urban structure. Under the assumption that, conditional on these fixed effects and observable controls, within-week variation in telework and cross-sectional structural exposure to telework are orthogonal to unobserved municipality-specific daily 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]

4.1.2 Work-to-Home Consumption Substitution Rate

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

[13] These fixed effects are crucial for identification, as spending follows systematic weekly cycles, with peaks on Wednesdays and Fridays (Online Appendix A.2, Figure OA.1). Including date $\times$ 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 (Table 10), 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.

[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.

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.

4.1.3 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:

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

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 4. 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.

[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: $\left|[\exp(\theta_1/\overline{\text{Workers}^{(\mathcal{H})}}) - 1]/[\exp(\theta_2/\overline{\text{Workers}^{(\mathcal{W})}}) - 1]\right|$ and approximately corresponds to $|\theta_1/\theta_2|$.

4.1.4 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.

4.2 Identification and Inference

Before turning to the results, we address three potential threats to their interpretation: whether θ_1 and θ_2 are separately identified given how the two telework regressors are constructed, how we account for the additional uncertainty this construction introduces, and how we address remaining concerns about measurement error and reverse causality.

Because both telework regressors are constructed by applying the same estimated daily component $\widehat{\beta}_t$ to municipality-specific structural weights—$\text{TE}_i^{(\mathcal{H})}$ for residential exposure and $\text{TE}_i^{(\mathcal{W})}$ for workplace exposure—one might worry that $\text{WFH}_{it}^{(\mathcal{H})}$ and $\text{WFH}_{it}^{(\mathcal{W})}$ are mechanically related, leaving little independent variation to separately identify θ_1 and θ_2. Separate identification in fact relies on cross-sectional variation in the divergence between these two structural weights: municipalities differ substantially in how their residential telework exposure compares to their workplace telework exposure, ranging from "bedroom" municipalities where $\text{TE}_i^{(\mathcal{H})} \gg \text{TE}_i^{(\mathcal{W})}$ to employment centers where the reverse holds. Condition-number diagnostics on the regression Hessian (ranging from 4 to 15 across specifications, well below the conventional threshold of 30) confirm that multicollinearity is not a first-order concern, and Appendix C.1 shows that our estimates of θ_1 and θ_2 remain stable and statistically significant when the sample is restricted to municipalities with the most extreme divergence between residential and workplace exposure, ruling out mechanical mirroring as the source of our results.

A related but distinct challenge concerns inference rather than identification. The variables $\text{WFH}_{it}^{(\mathcal{H})}$ and $\text{WFH}_{it}^{(\mathcal{W})}$ are generated regressors, as they depend on the first-step estimates $\widehat{\beta}_t$ from Equation 3, which are themselves estimated with uncertainty. Conventional standard errors that treat these regressors as known would understate the true uncertainty in our estimates, particularly for nonlinear functions of the coefficients such as the work-to-home substitution rate and the aggregated telework effects. To address this, we implement a two-stage bootstrap procedure (detailed in Appendix C.4) that resamples municipalities with replacement, re-estimates the first-step telework model, reconstructs the telework regressors, and re-estimates the consumption model in each iteration. This procedure accounts for both sampling variation and the additional uncertainty introduced by the generated regressors, providing more reliable inference for all parameters of interest. Standard errors for the work-to-home consumption substitution rate are additionally computed using the Delta Method (Pierce, 1982). The resulting confidence intervals are reported alongside the consumption substitution rates (Table 2) and the aggregated net effects (Table 3).

Beyond these two concerns, measurement error in our telework indicators and potential reverse causality remain possible sources of endogeneity. We address both via a shift-share instrumental variable strategy, described below; the corresponding results are presented alongside our baseline PPML estimates in Section 4.3.1.

Instrumental variable strategy. To assess the robustness of our PPML estimates to endogeneity—including measurement error in our constructed telework indicators and potential reverse causality—we implement an instrumental variable (IV) approach. This strategy follows a shift-share design, which is particularly suited to our setting as it isolates plausibly exogenous variation in telework exposure.

The instrument combines two components. The share component is constructed by interacting pre-COVID occupational telework propensities (from the 2017 estimates reported in Hallepée et al. (2019, Table 1), based on survey data from *Enquête Sumer 2017*) with historical residence–workplace–occupation matrices from the 1999 (and 2010) population censuses. This yields a predetermined time-invariant measure of a municipality's structural exposure to telework, which is unlikely to be correlated with daily consumption shocks in 2022. The shift component captures daily deviations in telework intensity, net of regular variation in non-working time, defined as the difference between our estimated daily working-from-home rates ($\widehat{\beta}_t$) and the daily day-off rates of a comparison group of part-time executives ($\gamma_{k=\textbf{executives},t}$). The latter provides a benchmark for regular within-week variation in home presence: part-time executives have a similar weekly pattern of non-working days to teleworkers (see Table 1 and Online Appendix, Figure OA.3), and their average number of non-working days per week (1.4; see Online Appendix, Figure OA.3) is close to the pre-COVID average number of teleworked days (1.9; see Online Appendix, Table OA.4). This shift term proxies for unanticipated changes in home presence that are plausibly orthogonal to local spending decisions, as it largely reflects firms' and workers' scheduling decisions (e.g., the peak in telework on Mondays, Wednesdays and Fridays) rather than contemporaneous demand conditions. Formally, the instruments are defined as:

$$Z_{it}^{(\mathcal{H})} = \left[\widehat{\beta}_t - \gamma_{k=\text{executives},t}\right] \times \text{TE}_{i,1999}^{(\mathcal{H})} \tag{5}$$

$$Z_{jt}^{(\mathcal{W})} = \left[\widehat{\beta}_t - \gamma_{k=\text{executives},t}\right] \times \text{TE}_{j,1999}^{(\mathcal{W})} \tag{6}$$

where $\text{TE}_{i,1999}^{(\mathcal{H})}$ and $\text{TE}_{j,1999}^{(\mathcal{W})}$ are computed using the 1999 census (and alternatively the 2010 census) instead of the 2021 census, and $\gamma_{k=\text{executives},t}$ is the daily day-off rate of part-time executives.

We implement this IV approach through a Two-Stage Residual Inclusion (2SRI) procedure, which is appropriate for our non-linear PPML framework (Wooldridge, 2015). In the first stage, each potentially endogenous telework indicator is regressed on the instruments and all exogenous covariates. The residuals from these regressions are then included as additional controls in the second-stage PPML estimation, providing a diagnostic for the presence of endogeneity. The corresponding second-stage 2SRI estimates, together with the resulting diagnostics, are reported and discussed in Section 4.3.1.

4.3 Baseline Results: Asymmetric Demand Shocks and Substitution Rates

4.3.1 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. Column 7 incorporates the full set of controls, which is our preferred PPML specification, although including these controls does not substantially alter the main coefficients, supporting their robustness. Column 8 reports the corresponding instrumental-variable estimates using the 1999 instrument vintage, constructed as described in Section 4.2.

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Transaction count								
$\text{WFH}^{(\mathcal{H})}$	1.147***	0.984***	1.150***	1.151***	1.146***	1.024***	0.985***	1.25***
	(0.226)	(0.217)	(0.223)	(0.223)	(0.224)	(0.227)	(0.213)	(0.357)
$\text{WFH}^{(\mathcal{W})}$	-1.736***	-1.738***	-1.717***	-1.720***	-1.732***	-1.668***	-1.713***	-2.34***
	(0.383)	(0.377)	(0.376)	(0.375)	(0.386)	(0.389)	(0.372)	(0.411)
$\text{PT}^{(\mathcal{H})}$		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)		
$\text{Residuals}^{(\mathcal{H})}$								0.336
								(0.499)
$\text{Residuals}^{(\mathcal{W})}$								1.02**
								(0.424)
Fit statistics								
Observations	10,640	10,640	10,640	10,640	10,640	10,640	10,640	10,600
BIC	166,692.0	166,326.0	166,657.1	166,662.6	166,645.0	166,472.2	166,239.7	166,376.4
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***	1.44***
	(0.269)	(0.281)	(0.266)	(0.266)	(0.270)	(0.289)	(0.279)	(0.412)
$\text{WFH}^{(\mathcal{W})}$	-1.363***	-1.359***	-1.350***	-1.353***	-1.363***	-1.288***	-1.343***	-2.19***
	(0.391)	(0.402)	(0.387)	(0.386)	(0.393)	(0.389)	(0.401)	(0.640)
$\text{PT}^{(\mathcal{H})}$		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)		
$\text{Residuals}^{(\mathcal{H})}$								0.022
								(0.616)
$\text{Residuals}^{(\mathcal{W})}$								1.16
								(0.777)
Fit statistics								
Observations	10,640	10,640	10,640	10,640	10,640	10,640	10,640	10,600
BIC	5,434,199	5,407,037	5,433,320	5,433,133	5,433,321	5,428,426	5,404,987	5,418,953
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. Columns (1)-(7) report PPML estimates, which constitute our primary specification. Column (8) reports 2SRI-IV estimates using the 1999 instruments as confirmatory evidence, discussed in Section 4.2. Inference for the work-to-home consumption substitution rate and the aggregated telework effects is based on a two-stage bootstrap procedure (see Appendix C.4) that accounts for the estimation error in the first-step telework regressors. 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. Column 8 reports second-stage 2SRI instrumental-variable estimates using the 1999 shift-share instruments, with control-function residuals ($\text{Residuals}^{(\mathcal{H})}$, $\text{Residuals}^{(\mathcal{W})}$) included as diagnostics for endogeneity. Full first-stage diagnostics and results using the 2010 instrument vintage are provided in Appendix C.3.

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 in our preferred PPML specification (column 7, significant at the 1% level); the corresponding 2SRI-IV estimate (column 8) is larger, at 1.25%, consistent with classical measurement error attenuating the PPML coefficient toward zero rather than inflating it. 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 under PPML, against a larger 2.34% and 2.19% decrease, respectively, under IV. These asymmetric effects highlight how telework simultaneously stimulates and suppresses local economic activity, with the negative workplace shock outweighing the positive residential shock in both specifications.[17]

The IV estimates rest on a shift-share design, described in Section 4.2 and implemented via a 2SRI procedure using the 1999 instrument vintage; full first-stage diagnostics and results using the 2010 vintage are reported in Appendix C.3. The instruments are strongly correlated with the endogenous telework variables, with first-stage Wald statistics ranging from 30.8 to 40.1, and redundancy tests following Borusyak et al. (2025) show that, conditional on the endogenous regressors, the instruments carry no additional explanatory power for local consumption—supporting the exclusion restriction. Both coefficients retain their sign and significance under IV, which makes it unlikely that endogeneity is the primary driver of our results.

This same comparison of coefficient magnitudes also speaks to a related but distinct concern: whether daily, individual-level consumption planning drives telework choices—for instance, deciding to work from home on a day when household errands are already planned—rather than the reverse. This channel operates at the individual level, whereas our identification strategy exploits variation aggregated at the municipality-day level; for it to bias our estimates, it would need to be systematically correlated with municipalities' structural telework exposure ($\mathrm{TE}_i^{(\mathcal{H})}$) rather than simply exist among some individuals, since our date-by-zone fixed effects already absorb any shock to consumption needs common to residents of a given zone on a given day. If this channel were a dominant source of bias, we would expect it to inflate—not attenuate—the baseline PPML coefficients relative to the IV estimates, which correct for it. We observe the opposite pattern here as well.

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. We assess this substitution rate drawing on three complementary sources of evidence, presented below: point estimates with Delta-Method inference, an instrumental-variable check against endogeneity, and a bootstrap procedure that further accounts for uncertainty in the generated telework regressors.

In our preferred PPML specification (column 7), 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

[17] Table 10 in Appendix C.2 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.

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 IV point estimates are of similar magnitude—0.53 for transaction counts and 0.66 for transaction values (1999 instrument)—though the corresponding 90% confidence intervals are considerably wider than under PPML and include unity for both outcomes ([0.34; 1.05] and [0.27; 1.77], respectively; Appendix C.3). This is consistent with the PPML point estimates, but the IV specification alone cannot rule out complete substitution, reflecting the loss of precision inherent to the 2SRI procedure and its slightly restricted sample.

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.

To provide rigorous inference on the degree of consumption reallocation, we compute standard errors using the Delta Method (Pierce, 1982), accounting for the nonlinearity of substitution rates. For transaction frequency, the 90% confidence interval [0.36; 0.79] lies significantly below unity, indicating incomplete substitution between workplace and home consumption and a decline in consumer visits due to telework. In contrast, for transaction values, the 90% confidence interval [0.40; 1.05] includes 1, suggesting substantial heterogeneity across municipalities: in some cases, residential consumption fully offsets workplace losses, while in others it does not. This highlights the importance of disaggregated analysis and suggests that telework primarily affects the spatial distribution of spending rather than aggregate consumption.

To provide a more accurate assessment of uncertainty for the work-to-home consumption substitution rate, we complement the Delta Method with a bootstrap procedure (Appendix C.4). Because the substitution rate is a nonlinear function of θ_1 and θ_2, its bootstrap mean need not coincide exactly with the Delta-Method point estimate reported above; both are reported for completeness. Online Appendix D.4, Figure OA.16, presents the distribution of the consumption substitution rate in both percentage points and units, while Table 14 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 confirms incomplete consumption substitution. For transaction

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

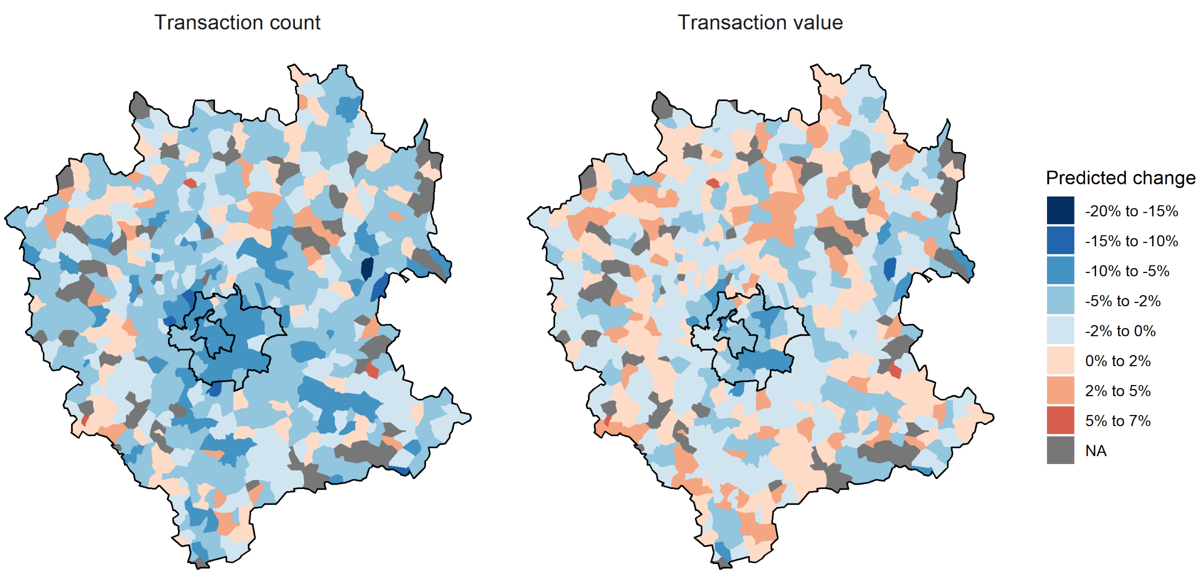
[19] Descriptive statistics for the variables of interest are reported in Table 8.

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.

To summarize, three complementary approaches point to a consistent pattern: substitution is incomplete for transaction frequency (the 90% CI lies below unity under both Delta Method and bootstrap, and the IV point estimate is consistent with this), while for transaction value, substitution is statistically compatible with near-full compensation across all three approaches.

4.3.2 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.



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 $(\hat{y}_{it} - \hat{y}^0_{it})/\hat{y}^0_{it}$, where $\hat{y}_{it}$ denotes the model-predicted values for municipality i at date t, and $\hat{y}^0_{it}$ denotes the corresponding predicted values under a zero-telework scenario. Predictions are obtained from our preferred PPML specification (column 7 of Table 2), which includes municipality fixed effects, date-by-zone-type fixed effects, and the full set of control variables.

Figure 4: Predicted Daily Change in Transaction Counts and Values Across the Lyon FUA

Result 3. Telework leads to a spatial redistribution of consumption. Figure 4 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].

We assess the significance of telework effects at the municipality level using the bootstrap procedure described in Section 4.2. Figure 11 maps statistically significant (10% level) average effects on transaction frequency and value, Table 15 summarizes their distribution, and Table 16 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.

Two patterns stand out. First, significant effects are roughly twice as prevalent for transaction frequency (168 of 532 municipalities, 31.6%) as for transaction value (70 of 532, 13.2%), reflecting the higher precision of the frequency estimates documented in Result 2. Second, while the majority of municipalities have negative point estimates for transaction value, the subset that reaches statistical significance is predominantly positive. This apparent contradiction is resolved by the imprecision of the value estimates: only the largest positive shifts—concentrated in residential municipalities—are sufficiently large to be distinguished from zero, whereas the more numerous but smaller negative shifts remain imprecisely estimated.

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 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%), and urban commuting zone (-4.8%)—all statistically significant at the 90% level. The decline in the rural commuting zone (-2.7%) is smaller and not statistically distinguishable from zero. Observed decreases in transaction values are smaller (from -1% to -3.3%), but not statistically significant at the zone-group 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. To put these effects in perspective, aggregating the statistically significant decline in transaction counts over a full year of weekdays (approximately 250 working days)

[20]Online Appendix D.2, Figure OA.13, 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, Online Appendix D.1, Figures OA.8-OA.12

[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.4, and the corresponding results are presented in Table 13.

implies a reduction of roughly 10.5 million transactions annually across the Lyon FUA. In value terms, the point estimate corresponds to approximately €171 million per year, equivalent to 2.6% of annual weekday offline consumption in the area (approximately €6.5 billion); however, this value effect is not statistically distinguishable from zero, consistent with our finding that telework primarily reduces purchase frequency rather than aggregate spending.[22]

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.4, and the corresponding results are presented in Table 13.

Overall, aggregating across municipalities confirms the pattern documented in Result 3: telework redistributes consumer activity away from urban cores toward less dense areas, primarily through reduced visit frequency rather than a fall in aggregate spending. 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. The point estimate suggests a modest aggregate decline in transaction value of -2.6% (Table 3), but the 90% confidence interval (-7.1% to +2.6%) includes zero. We therefore cannot reject the hypothesis that aggregate spending is unchanged, consistent with near-complete substitution of spending from workplace to residence—though the interval leaves open a modest net decline as well.

[22] For comparison, Alipour et al. (2026) estimate a spending elasticity of -3.7% with respect to WFH-induced declines in morning commuting across 50 German metropolitan areas, a different unit of measurement from our telework-share elasticities, but a broadly comparable order of magnitude, lending external support to the scale of the effects we document.

4.4 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 Online Appendix C.1, Table OA.6.

4.4.1 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),[23]. whereas rates above one in other sectors are not statistically different from unity (and even include values below unit in the bootstrap confidence intervals).

[23] Further details on the bootstrap procedure are provided in Appendix C.4, and the corresponding results are presented in Online Appendix E.1, Table OA.15

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.4, and the corresponding results are presented in Online Appendix E.1, Table OA.15.

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.

Other sectors show more limited but not uniformly absent effects. General Retail exhibits significant negative responses to workplace absence for both counts (-1.2%, $p < 0.05$) and values (-1.0%, $p < 0.1$), though its substitution rate is imprecisely estimated. Recreation displays a large workplace-absence coefficient in value terms (-5.7%, $p < 0.05$), with a substitution rate of 0.52 ($p < 0.05$), indicating incomplete substitution similar in kind to Restaurants but concentrated in value rather than frequency. Health shows a comparable pattern for counts (substitution rate: 0.36, $p < 0.05$). Only Clothing shows no significant response along either margin. 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 is consistent with 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 Online Appendix A.2, Figure OA.2) but significantly affects sectors with opposing consumption patterns. This differential impact is consistent with our estimates capturing telework-induced changes in economic activity, rather than spurious correlations.

4.4.2 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 Online Appendix E.1, Table OA.14. 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 Online Appendix E.1, Figures OA.17-OA.20, for the estimated net effects on maps; see Online Appendix E.1, Figure OA.23, 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 Online Appendix E.1, Figures OA.21-OA.22): 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.

Online Appendix E.1, Tables OA.16 and OA.17, further document the spatial heterogeneity in the sectoral impact of telework. Table OA.16 reports the distribution of the average net effect of telework across municipalities for the subset with statistically significant estimates. Table OA.17 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 Online Appendix E.1, Figure OA.23). 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.

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

		Transaction count			Transaction value		
	(1) N_g	(2) $\sum_{i\in g} y_{ig}$	(3) Δ_g %	(4) Δ_g	(5) $\sum_{i\in g} y_{ig}$	(6) Δ_g %	(7) 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.4, and the corresponding results are presented in Online Appendix E.1, Table OA.14.

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.

4.5 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. 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 support our identification strategy and are not consistent with our findings being driven by 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, thereby eliminating any risk of double-counting bias. The exceptional stability of coefficients in our telecommuter-specific models (Online Appendix C.2, Table OA.7) supports that our findings are not artifacts of measurement construction. As anticipated in Section 4.2, we further verify that our estimates of θ_1 and θ_2 are not driven by mechanical mirroring between home-presence ($\mathrm{WFH}^{(\mathcal{H})}$) and workplace-absence ($\mathrm{WFH}^{(\mathcal{W})}$) by restricting 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 9, the estimated effects remain stable and significant across different quantiles selection, consistent with the model capturing 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. Online Appendix C.6, Figure OA.6, 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 (Online Appendix C.6, Table OA.9), while another approach employs finer geographic resolution measures (method described in Online Appendix C.6, results in Table OA.10). 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.

Identification strategies. Third, we implement additional identification strategies to strengthen the causal interpretation of our findings. Our shift-share instrumental variable strategy, described in Section 4.2 and presented alongside the corresponding results in Section 4.3.1, provides strong confirmatory evidence for our PPML findings. As documented in Appendix C.3, the instruments pass standard relevance and redundancy tests, and results are consistent across the 1999 and 2010 instrument vintages. As a final complement, we implement an alternative strategy relying solely on spatial variation in telework potential across municipalities (Online Appendix C.7, Table OA.11). While this approach yields less precise estimates, the directional consistency with our main results further confirms the robustness of our findings.

5 Beyond the Baseline: Model Extensions

This section examines two dimensions of telework's impact on local consumption that remain largely overlooked in the literature: spatial spillovers and intertemporal substitution. We first estimate whether telework in one municipality affects consumption in adjacent municipalities, capturing the extent to which telework reshapes consumption beyond workers' residential and workplace locations. This spillover channel is particularly relevant given that 12.0% of potential teleworkers commute to a municipality adjacent to their residence (see Section 3.1), providing a direct empirical basis for examining consumption effects in neighboring municipalities. We then examine whether telework alters the temporal distribution of consumption between weekdays and weekends. By reducing commuting time on telework days, telework may free up time for purchases during the week that would otherwise be made on weekends. Such intertemporal substitution would leave total consumption unchanged while reallocating spending across days. Ignoring this channel could therefore affect the interpretation of the baseline estimates: an increase in weekday spending may reflect a re-timing of purchases rather than an increase in overall consumption.

5.1 Spatial Spillovers: How Telework Redistributes Consumption Across Municipalities

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

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

$$Y_{it} = \exp\left[\theta_1 \mathrm{WFH}_{it}^{(H)} + \theta_2 \mathrm{WFH}_{it}^{(W)} + \lambda_1 \sum_{j \neq i} w_{ij} \mathrm{WFH}_{jt}^{(H)} + \lambda_2 \sum_{j \neq i} w_{ij} \mathrm{WFH}_{jt}^{(W)} + \delta_i + \gamma_{gt} + \epsilon_{it}\right] \quad (7)$$

where $\sum_{j \neq i} w_{ij} \mathrm{WFH}_{jt}^{(\cdot)}$ 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.[24] The estimation results for model 7 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 7, reported in Table 6, provide evidence of both direct and spatial spillover effects of telework on local consumption activity. We find significant effects of telework shares in neighboring municipalities on transactions' count and value. A one-percentage-point increase in telework-induced presence at home in neighboring areas, $\mathrm{WFH}_{\text{neighbors}}^{(\mathcal{H})}$, 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, $\mathrm{WFH}_{\text{neighbors}}^{(\mathcal{W})}$, 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).

[24] 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.

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.[25]). The direct positive effects of residential telepresence are statistically significant only in Lyon city and the rest of the urban core, whereas the negative effects of workplace absence are evident across all zones, with the strongest impacts observed in Lyon. Indirect effects from telepresence in neighboring municipalities are significant only for Lyon city, suggesting higher consumption mobility among its residents. Additionally, workplace absence in neighboring areas negatively affects both Lyon and the rest of the urban core, with Lyon experiencing the largest declines. These findings indicate that teleworkers with offices in the urban core often consume in surrounding areas when physically present at work, so reduced workplace attendance negatively impacts neighboring municipalities. This aligns with the trip-chaining behavior documented by Miyauchi et al. (2025). Notably, indirect spillover effects are often comparable to, or even exceed, direct effects, likely due to the prevalence of trip chaining in dense commuting areas.

[25]Significant spatial heterogeneity in telework's spillover effects across the Lyon Functional Urban Area (FUA) is also existing (see Online Appendix F, Table OA.18

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[26] 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:

$$\begin{aligned} Y_{ot} = \exp\Big[&\sigma_1 \, \mathrm{TE}_o^{(\mathcal{H})} + \sigma_2 \, \mathrm{Weekend}_t + \sigma_3 \, \mathrm{TE}_o^{(\mathcal{H})} \times \mathrm{Weekend}_t \\ &+ \sigma_4 \, \log(\mathrm{Population}_o) + \varepsilon_{ot}\Big] \end{aligned} \tag{8}$$

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 identification is based on within-municipality variation over time in consumption. We further control for consumption dynamics associated with the urban structure of municipalities by including date-by-urban-group fixed effects, which net out common shocks at the urban-group level and allow comparisons across municipalities within the same urban group at a given date. As a result, identification relies on two sources of variation: (i) within-municipality temporal variation in consumption, and (ii) cross-municipality variation in telework

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

prevalence across municipalities belonging to the same urban group, conditional on date-specific shocks at that level. The estimation results for model 8 are reported in columns 1 and 2 of Table 7.

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

$$\begin{aligned}
Y_{odt} = \exp \Big[& \lambda_1 \, \mathrm{TE}_o^{(\mathcal{H})} + \lambda_2 \, \mathrm{Weekend}_t + \lambda_3 \, \mathrm{Home}_{od} \\
& + \lambda_4 \, \mathrm{TE}_o^{(\mathcal{H})} \times \mathrm{Home}_{od} \\
& + \lambda_5 \, \mathrm{Weekend}_t \times \mathrm{Home}_{od} \\
& + \lambda_6 \, \mathrm{TE}_o^{(\mathcal{H})} \times \mathrm{Weekend}_t \\
& + \lambda_7 \, \mathrm{TE}_o^{(\mathcal{H})} \times \mathrm{Weekend}_t \times \mathrm{Home}_{od} \\
& + \lambda_8 \, \log(\mathrm{Population}_o) + \varepsilon_{odt} \Big]
\end{aligned} \tag{9}$$

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 and date by urban group fixed effects, which capture common shocks affecting all municipalities of a same urban group on a given day. The estimation results for model 9 are reported in columns 3 and 4 of Table 7.

Table 7: Intertemporal consumption substitution induced by telework

	Transactions$_{ot}$			Transactions$_{odt}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Transaction count						
TE$^{(\mathcal{H})}$	0.539			-11.800***		
	(1.120)			(0.510)		
Weekend	-0.048			0.000***		
	(0.031)			(0.000)		
log(Pop)	1.210***			1.210***		
	(0.061)			(0.061)		
TE$^{(\mathcal{H})}$ × Weekend	-0.339**	-0.330**	0.053	-0.000***	-0.000**	0.272**
	(0.159)	(0.154)	(0.171)	(0.000)	(0.000)	(0.117)
Home				19.700***	23.000***	23.000***
				(0.175)	(0.008)	(0.007)
TE$^{(\mathcal{H})}$ × Home				12.400***	14.600***	14.700***
				(0.874)	(0.041)	(0.035)
Weekend × Home				-0.049	-0.146***	-0.163***
				(0.031)	(0.030)	(0.025)
TE$^{(\mathcal{H})}$ × Weekend × Home				-0.335**	-0.329**	-0.217
				(0.159)	(0.154)	(0.135)
Fixed-effects						
Week	✓			✓		
Postcode		✓	✓		✓	✓
Date		✓			✓	
Date × urban group			✓			✓
Fit statistics						
Observations	4,144	4,144	4,144	8,219	8,219	8,219
BIC	1,129,433	67,399	62,381	1,125,199	67,223	62,271
Panel B: Transaction value						
TE$^{(\mathcal{H})}$	-0.926			-11.300***		
	(1.350)			(0.637)		
Weekend	-0.043			0.000***		
	(0.039)			(0.000)		
log(Pop)	1.150***			1.150***		
	(0.076)			(0.076)		
TE$^{(\mathcal{H})}$ × Weekend	-0.159	-0.159	-0.164	0.000***	0.000***	0.020
	(0.204)	(0.203)	(0.243)	(0.000)	(0.000)	(0.141)
Home				19.600***	22.600***	22.600***
				(0.211)	(0.011)	(0.009)
TE$^{(\mathcal{H})}$ × Home				10.300***	14.100***	14.100***
				(1.070)	(0.055)	(0.049)
Weekend × Home				-0.044	-0.192***	-0.189***
				(0.039)	(0.039)	(0.033)
TE$^{(\mathcal{H})}$ × Weekend × Home				-0.153	-0.158	-0.183
				(0.205)	(0.202)	(0.180)
Fixed-effects						
Week	✓			✓		
Postcode		✓	✓		✓	✓
Date		✓			✓	
Date × urban group			✓			✓
Fit statistics						
Observations	4,144	4,144	4,144	8,219	8,219	8,219
BIC	57,342,020	1,883,442	1,695,005	57,154,685	1,868,714	1,680,582

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

Result 8. Telework and intertemporal consumption patterns: no robust evidence of substitution between weekdays and weekends. Table 7 columns 1-3 present estimates from the PPML regressions where the dependent variable is the number (Panel A) and the value (Panel B) of daily transactions aggregated at the residential postcode level. The interaction term $\text{TE}^{(\mathcal{H})} \times$ Weekend captures whether the intensity of telework is associated with a redistribution of consumption toward or away from weekends. In specifications without date-by-urban-group fixed effects, we find that this coefficient is negative and statistically significant, suggesting that municipalities with higher telework intensity exhibit lower weekend consumption. This pattern is consistent with an intertemporal substitution mechanism, whereby telework allows individuals to shift part of their expenditures—such as grocery shopping or household-related purchases—from weekends to weekdays. However, this result is not robust to the inclusion of date-by-urban-group fixed effects, which absorb differential temporal dynamics across urban and rural areas. Once these group-specific time shocks are accounted for, the coefficient becomes statistically insignificant, indicating that the previously observed effect is largely driven by heterogeneous consumption dynamics across urban groups rather than within-group reallocation of spending over time.

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 4-6 in Table 7 reveal several key insights. Column 5 estimates a specification with postcode fixed effects and date fixed effects, allowing identification from within-postcode variation over time and cross-postcode differences at a given date. In this specification, the triple interaction term $\text{TE}^{(H)} \times$ Weekend $\times$ Home is negative and statistically significant, while the coefficient $\text{TE}^{(H)} \times$ Weekend is zero. This suggests that, conditional on these fixed effects, higher telework intensity is associated with a relative reduction in weekend home transactions compared to weekdays within the same postcode, consistent with a potential intertemporal substitution pattern in consumption timing. However, this result is not robust to the inclusion of date-by-urban-group fixed effects (Column 6). The estimates show a positive effect of telework intensity on weekend consumption outside the residential zone ($\text{TE}^{(H)} \times$ Weekend), while a corresponding (though not statistically significant) negative effect is observed at the place of residence ($\text{TE}^{(H)} \times$ Weekend $\times$ Home). At the same time, the positive coefficient on $\text{TE}^{(H)} \times$ Home indicates that telework is associated with a general increase in home-originated transactions, consistent with our baseline results.

Beyond the weekday/weekend margin examined above, we also explored whether telework induces substitution in consumption timing across adjacent weekdays—for instance, if teleworkers shift errands to the day preceding a high-telework day.[27] The exercise proved inconclusive: constructing lagged telework shares raises a mechanical identification challenge, since $\text{WFH}_{it}^{(\mathcal{H})} = \widehat{\beta}_t \times \text{TE}_i^{(\mathcal{H})}$ by construction, and $\widehat{\beta}_t$ follows a near-deterministic weekly calendar (Table 1) over our four-week sample, leaving little variation in the lagged share that is independent of the contemporaneous one. We therefore do not treat this exercise as informative about day-to-day substitution one way or the other. As discussed in Section 4 in relation to reverse causality, this margin does not threaten our main identification strategy unless it is itself correlated with municipalities' structural telework exposure, which our exploratory tests do not establish.

Overall, these results suggest that telework primarily induces a spatial reallocation of weekday and weekend consumption rather than a change in its aggregate level or timing. Residential-area transactions increase with the concentration of resident teleworkers during weekdays, while non-residential-area transactions increase during weekends. This weekend pattern may reflect that

[27] We regress transaction outcomes on leads and lags of $\text{WFH}_{it}^{(\mathcal{H})}$ and $\text{WFH}_{it}^{(\mathcal{W})}$; results not reported for brevity.

telework increases individuals' propensity to engage in out-of-home activities during weekends, as they spend more time at home during the week, thereby reducing fatigue associated with weekday commuting.

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. 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). These effects retain their sign and significance under an instrumental-variable strategy exploiting shift-share variation in structural telework exposure. Second, we provide the first empirical evidence of incomplete substitution between home- and workplace-based consumption in terms of transaction frequency: home-based gains offset only about 57% of workplace losses, a gap that is statistically significant. For transaction value, the estimated substitution rate (72%) is not statistically distinguishable from unity; this is corroborated by our aggregate-level results (Result 4), which show no statistically significant net effect on total spending, though the width of the confidence interval does not rule out a modest net decline. 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.[28] This heterogeneity suggests that targeted policies

[28]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.

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 and absence from the workplace), or shifts in savings, investment, and broader consumption behavior. In the same vein, our study period (September 2022) may still reflect some transitional dynamics from the pandemic. However, telework adoption had already largely stabilized by this point: the share of teleworkers rose sharply from 3% in 2017 to about 19-22% in 2021-2022, and has since remained close to this level (18.3-18.4% in 2023-2024, Online Appendix Table OA.4), suggesting that our estimates capture a durable feature of the post-pandemic labor market rather than a transient disruption. Third, our analysis captures in-person transactions only. Online channels—food delivery platforms and grocery e-commerce—could in principle recapture some of the spending we classify as lost, which would lead our substitution rate to understate the true recovery of spending. To bound this concern, we conduct a simple sensitivity exercise. Even under the conservative assumption that 20% of the restaurant spending not already recaptured through increased in-person consumption near the residence is fully recovered through delivery, the implied substitution rate for transaction counts rises from 0.27 to approximately 0.42[29], still well below unity. The threshold at which the substitution rate would reach unity is 100% of the residual loss being recovered online, a scenario in which every euro not spent in-person near the residence is fully redirected to delivery platforms. At the aggregate level, any spending recaptured through online channels would, if anything, reinforce rather than overturn our finding that the net effect on total spending is statistically indistinguishable from zero (Result 4). These bounds suggest that our main conclusions are not highly sensitive to the online channel, though they imply that our spatial redistribution estimates apply primarily to brick-and-mortar commerce.

Additionally, 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.

[29] Formally, if $s_0 = 0.27$ denotes the baseline substitution rate and $\delta = 0.20$ the assumed share of the residual loss $(1 - s_0)$ recaptured through delivery, the adjusted rate is $s_1 = s_0 + \delta(1 - s_0) = 0.27 + 0.20 \times 0.73 \approx 0.42$.

References

Alipour, J.-V., O. Falck, S. Krause, C. Krolage, and S. Wichert (2026). Working from Home and Consumption in Cities. SSRN Electronic Journal.

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

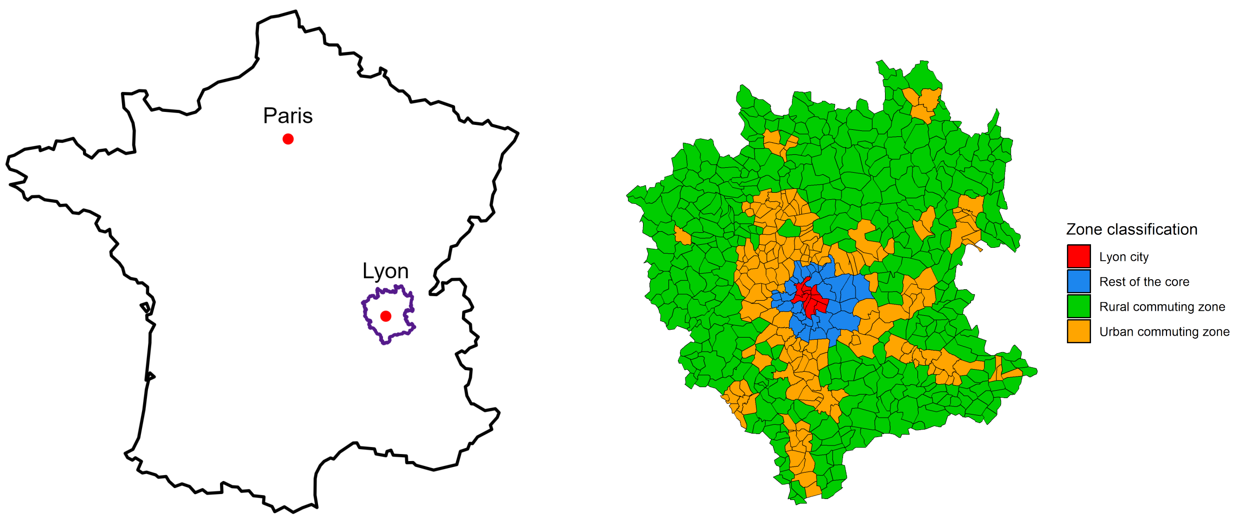
Territoires, G. P. (2022, February). Exode urbain. Un mythe, des réalités. Technical report, Groupement d'intérêt public interministériel européen des projets architecturaux et urbains, Programme POPSU Territoires.

Wooldridge, J. M. (2015, March). Control Function Methods in Applied Econometrics. Journal of Human Resources 50(2), 420–445.

A Appendix to Section 2

A.1 Lyon FUA and municipalities classification

Figure 5a illustrates the geographic context of the study by displaying a map of France with the Lyon Functional Urban Area (FUA) highlighted. Figure 5b 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 5: Maps of the Lyon Functional Urban Area and municipality classification.

Table 8: Summary statistics

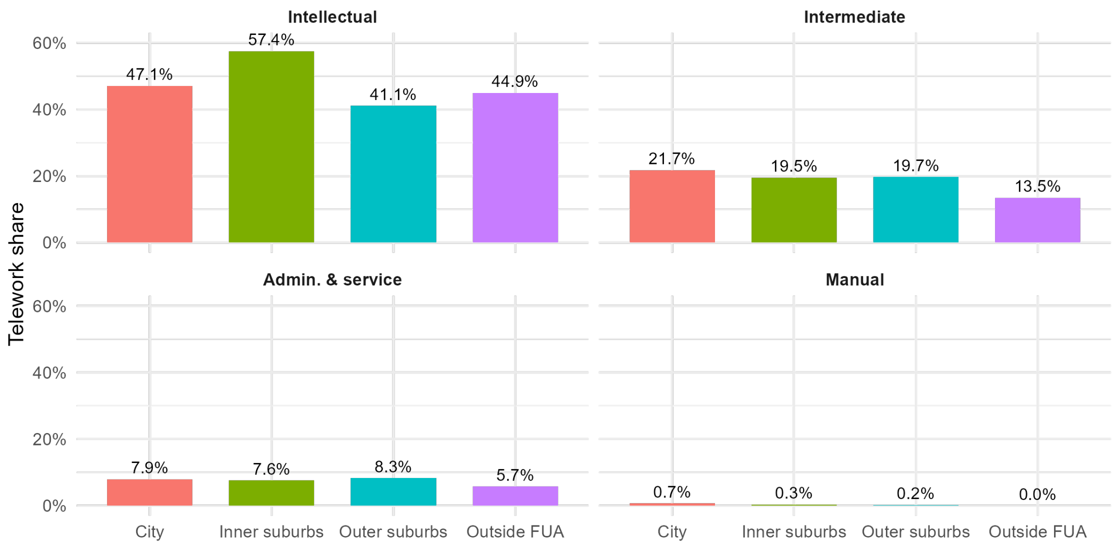
	Min	1Q	Median	Mean	3Q	Max	Sd
Transaction frequency$_{it}$	0.00	13.00	105.00	1,335.58	598.00	59134.00	4509.73
Transaction value$_{it}$	0.00	579.75	3,694.50	47,403.92	21,397.50	2,260,169.00	147,079.61
$\text{Workers}_i^{(\mathcal{H})}$	34.76	435.78	815.61	2,161.45	1,679.50	70,498.43	5,435.30
$\text{Workers}_i^{(\mathcal{W})}$	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
$\text{TE}_i^{(\mathcal{H})}$	5.21	12.43	14.91	15.42	17.80	31.87	4.12
$\text{TE}_i^{(\mathcal{W})}$	1.62	8.84	11.59	11.94	14.64	31.57	4.65
$\frac{\text{Teleworkers}_i^{(\mathcal{H})} - \text{Teleworkers}_i^{(\mathcal{W})}}{\text{Teleworkers}_i^{(\mathcal{H})} + \text{Teleworkers}_i^{(\mathcal{W})}}$	-0.87	0.18	0.49	0.41	0.67	0.95	0.35
$\text{Teleworkers}_i^{(\mathcal{H})} - \text{Teleworkers}_i^{(\mathcal{W})}$	-9,100.76	17.84	50.84	-12.18	104.62	2,420.55	659.85

Note: The table reports summary statistics at the municipality–weekday level. It includes transaction frequency and transaction value, as well as the resident worker population ($\text{Workers}_i^{(\mathcal{H})}$) and workplace-based workers ($\text{Workers}_i^{(\mathcal{W})}$). It also presents estimates of the number of teleworkers at home and at workplaces, both in levels and as shares of the corresponding populations ($\text{TE}_i^{(\mathcal{H})}$ and $\text{TE}_i^{(\mathcal{W})}$), the relative teleworkers residential-workplace imbalance, defined as $(\text{Teleworkers}_i^{(\mathcal{H})} - \text{Teleworkers}_i^{(\mathcal{W})})/(\text{Teleworkers}_i^{(\mathcal{H})} + \text{Teleworkers}_i^{(\mathcal{W})})$, capturing the degree of asymmetry between residential and workplace-based teleworker presence, and the absolute imbalance, defined as $\text{Teleworkers}_i^{(\mathcal{H})} - \text{Teleworkers}_i^{(\mathcal{W})}$, reflecting net differences in teleworker counts across municipalities.

B Appendix to Section 3: Telework Statistics

B.1 Telework shares by occupation and residence location

Figure 6 shows the different teleworkers shares among workers by occupation and residence municipality group within the FUA.



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*, fourth quarter of 2022.

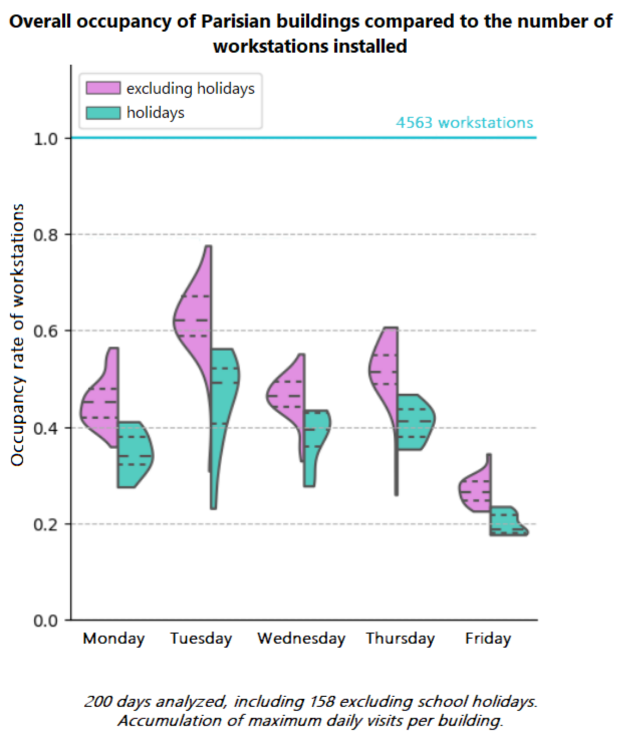
Figure 6: Telework shares by occupation and residence location within FUA

B.2 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 7, 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 of the main paper, 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 7: 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: Robustness Checks and Identification Strategies

This section presents the key robustness checks and identification strategies that support the causal interpretation of our main findings.

C.1 Divergence Test: Addressing the Mechanical Mirroring Concern

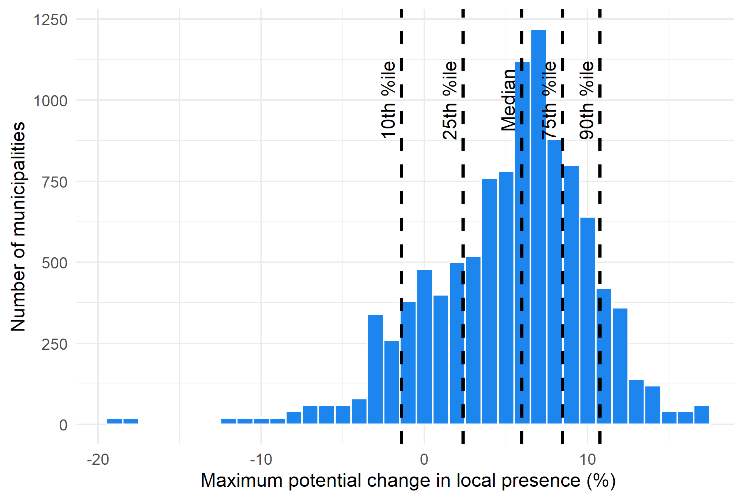
One might be concerned that identification relies on a mechanical relationship between home presence, $\mathrm{WFH}^{(H)}$, and workplace absence, $\mathrm{WFH}^{(W)}$. Both variables are constructed by projecting the same residential telework practices through commuting flows and multiplying by the 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 8 visualizes the distribution of $\Delta\%_{\text{presence}}$ across municipalities, highlighting substantial variation in potential telework-induced presence.



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.

Figure 8: Distribution of maximum potential change in local presence due to telework

The test consists in restricting the analysis to municipalities with different divergence intensity between residential and workplace exposure, based on the quantiles of $\Delta\%$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$50% for model 4). Table 9 shows that in municipalities with extreme divergences (columns 1–2), telework-induced home-presence significantly increases transactions ($\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.

Table 9: 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).

C.2 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 10 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. 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 10: Robustness check: two-way clustering of standard errors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Transaction count							
$WFH^{(\mathcal{H})}$	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)
$WFH^{(\mathcal{W})}$	-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)
$PT^{(\mathcal{H})}$		1.66					1.66
		(1.06)					(1.04)
$PT^{(\mathcal{W})}$		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)
$WFH^{(\mathcal{H})}$ × Public transp. disrupt.						0.720	
						(0.489)	
Public transp. disrupt. × $WFH^{(\mathcal{W})}$						-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							
$WFH^{(\mathcal{H})}$	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)
$WFH^{(\mathcal{W})}$	-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)
$PT^{(\mathcal{H})}$		0.8377					0.8487
		(1.025)					(1.024)
$PT^{(\mathcal{W})}$		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)
$WFH^{(\mathcal{H})}$ × Public transp. disrupt.						0.7002**	
						(0.3235)	
Public transp. disrupt. × $WFH^{(\mathcal{W})}$						-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.

C.3 Instrumental Variable Approach

To mitigate the potential bias from measurement error and endogeneity, 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.

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 and 2010 population censuses. 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. This variation is plausibly unrelated to daily consumption, providing a credible source of exogenous variation to identify the causal effects of telework.

Tables 11 and 12 report the 2SRI IV estimation results for the effect of telework on transaction counts and values, respectively, using the 1999 and 2010 instruments. 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 relative to the 2010 instruments. All effects are highly significant (see Figures 9 and 10 for bootstrapped confidence intervals based on 1,000 iterations).

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, 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 is 0.53 using the 1999 instrument and 0.37 using the 2010 instrument for transaction counts, and 0.66 and 0.42, respectively, for transaction value—below the baseline estimates of 0.66 and 0.78. The stability of these estimates across identification strategies provides corroborating support for our identification strategy.

Table 11: 2SRI results, 1999 instruments

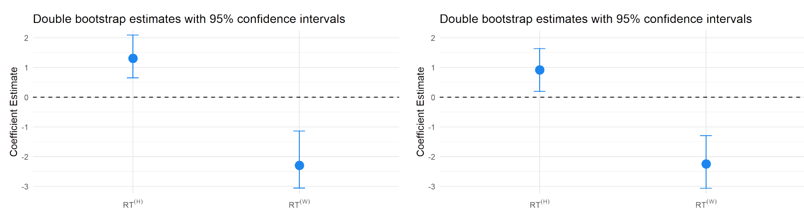
Dependent Variables:	WFH$^{(\mathcal{H})}$	WFH$^{(\mathcal{W})}$	WFH$^{(\mathcal{H})}$	WFH$^{(\mathcal{W})}$	Transaction count			Transaction value		
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Relevance test		First-stage		Baseline	Second-stage	Redundancy	Baseline	Second-stage	Redundancy
	OLS	OLS	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 12: 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						

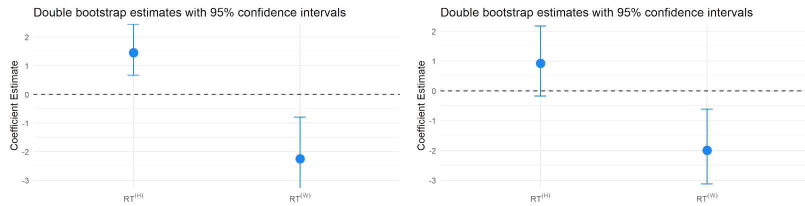
Note: Signif. codes: ***: 0.01, **: 0.05, *: 0.1. Clustered standard-errors at the municipality level in parentheses. All specifications include municipality and date-by-zone type fixed effects. The table presents a series of estimations examining the relationship between teleworking intensity and local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



(a) 1999 Instruments (b) 2010 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, and 2010. 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 9: Bootstrapped 2SRI coefficients and confidence intervals for transaction counts by instrument year



(a) 1999 Instruments (b) 2010 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, and 2010. 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 10: Bootstrapped 2SRI coefficients and confidence intervals for transaction values by instrument year

C.4 Quantifying the Net Economic Impact of Telework: Bootstrap Inference

To robustly assess the uncertainty surrounding our estimates of the consumption substitution rate and aggregated telework effects, 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 : $\left|\dfrac{\exp\left[\frac{\widehat{\theta_1}}{\text{Workers}^{(\mathcal{H})}}\right]-1}{\exp\left[\frac{\widehat{\theta_2}}{\text{Workers}^{(\mathcal{W})}}\right]-1}\right|$
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 the net aggregated effect of telework. Table 13 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 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.

Table 13: 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 14 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 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.

Table 14: 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.

Distribution of the net effect of telework by municipality. Table 15 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 10% level.

Table 15: Bootstrap distribution of average telework effects across municipalities

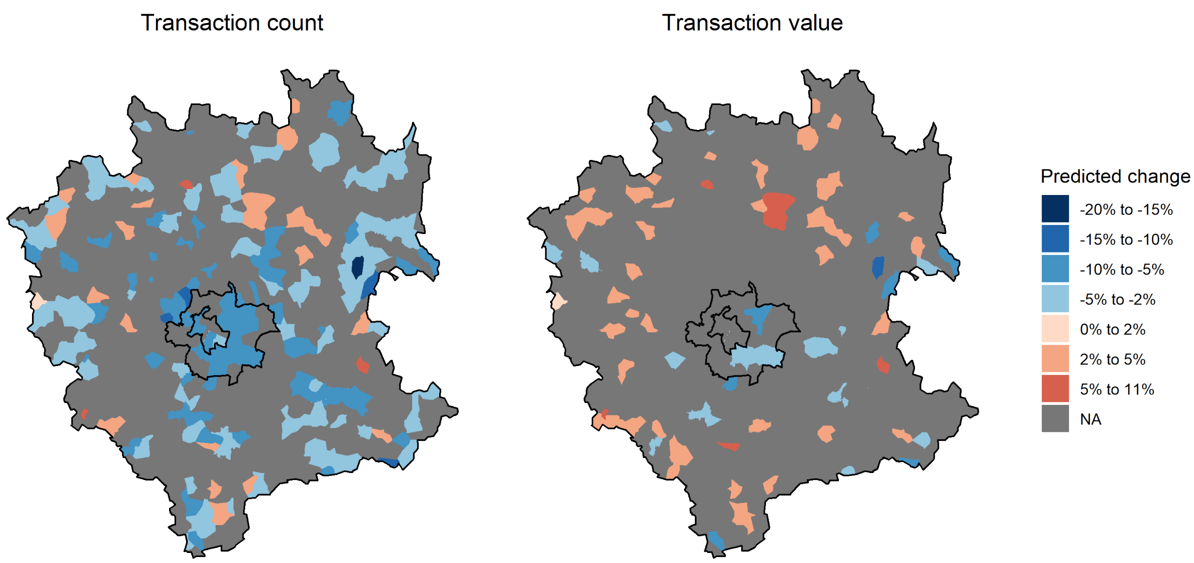
Sample	Min.	1st Qu.	Median	3rd Qu.	Max.	N
Panel A: Transaction frequency						
All	-15.608	-3.742	-2.077	-0.252	6.350	532
Significant positive	1.383	2.768	3.157	4.150	6.350	26
Significant negative	-15.608	-6.431	-4.966	-3.928	-2.446	142
Panel B: Transaction value						
All	-11.549	-1.680	-0.204	1.230	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 16: 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.



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 11: Statistically significant telework effect on transaction frequency and value