COVID-19 restrictions and workplace mobility: Synthetic control analysis using Google data

Caro, Juan Carlos and Gutierrez-Lythgoe, Antonio and Molina, Jose Alberto

IEDIS, Universidad de Concepción, Universidad de Zaragoza

February 2025

COVID-19 restrictions and workplace mobility: Synthetic control analysis using Google data

Juan Carlos Caro, Universidad de Concepción
Antonio Gutiérrez-Lythgoe, Universidad de Zaragoza
José Alberto Molina, Universidad de Zaragoza

February 2025

Abstract

The health mandated restrictions during the COVID-19 pandemic induced permanent changes in the economy and society worldwide. Transformation is mainly noticeable in economic sectors where daily tasks permit some degree of telework (e.g. call centers), and those which replaced in-person business (e.g. delivery services). COVID-19 restrictions in Europe implied a 160% increase in working from home (WFH), with a small decrease after mandated restrictions were removed. This paper employs synthetic control methods with Google data to analyze the casual impact of removing these restrictions on the workplace mobility in cities across four European countries (Spain, Italy, France and Sweden). Findings show a significant average fall of 6.3% in workplace mobility post-restriction relaxation. This result highlight associations with key factors such as COVID-19 cases, city population, sex-ratio, stringency index, and residential mobility, pointing towards a potential increase in remote work adoption. These findings underscore the intricate dynamics of workplace measures and their broader implications for evolving remote work trends.

JEL codes: C21, J22

Keywords: Workplace mobility; Generalized synthetic control methods; Remote work; Google data

Introduction

The COVID-19 pandemic was a strong catalyzer for technological development and adaptation in multiple economic sectors (Renu, 2021). Technological change was particularly important where core tasks required adaptation due to containment restrictions: remote work using connectivity platforms, new sanitary and safety protocols, contactless delivery services, automated processes, and tasks, among others. Many of such changes lead to increased prevalence for short and long term remote work arrangements (i.e. telework) (López Soler et al., 2023). The post-COVID impact on telework is estimated at 100% increase in the European Union, reaching one of every five workers in Europe today (Milasi et al., 2021). While at the country level the rates of telework (either partial or completely remote) vary around 15 percent of total employment, in large cities it reaches roughly half of the population. Jobs with higher autonomy and those involving high computer use are the most likely to experience some level of telework.

Working remotely, at least during the COVID-19 pandemic, has been perceived positively by workers and managers in Europe (Criscuolo et al., 2021), yet there are recent concerns regarding the long-term impact of telework on productivity (Emanuel & Harrington, 2023). Factors associated with lower productivity while working remotely include difficulties associated with training, on-the-job learning, creativity, and teamwork. Moreover, the experience of workers is also mixed. While employees value flexibility, increased concentration, and avoiding commuting, they also express concerns regarding isolation, ergonomics, and lack of clear separation between work and personal life. Teleworkers also tend to work more irregular hours and spend less time on market work compared to commuters, which could influence overall productivity and job satisfaction (Giménez-Nadal et al., 2020). A particular issue is presenteeism (working while sick), which could also potentially explain differences in productivity between remote and in-person work (Ferreira et al., 2022). Additionally, remote work has shown gender-specific effects, as time allocation and work-life balance dynamics evolved differently for men and women during lockdowns (Giménez-Nadal et al., 2024). The shift to home-based work also reinforced traditional gender roles within households, increasing the burden of domestic tasks and childcare responsibilities, particularly for women, and exacerbating financial and emotional stress in lower-income families (Andrade et al., 2022). Overall, while there are potential benefits from teleworking for society at large, impacts are quite heterogeneous, as a function of the job description, adequation of the working space, existing company culture, etcetera. Furthermore, a permanent increase in telework could exacerbate social and economic inequality at the global and local level.

The increasing use of digital technologies in recent years has opened the door to incorporating user-generated data into research, providing new opportunities to analyze human behavior at scale. Mobility data from digital devices offers a useful tool for studying telework, allowing for real-time, large-scale analysis that surpasses the limitations of traditional survey-based methodologies (Einav & Levin, 2014). Previous research has explored the use of user generated data in social media to assess teleworking dynamics during the COVID-19 pandemic (Dubey & Tripathi, 2020; Zhang et al., 2021; Daneshfar et al., 2022; Saura et al., 2022; Gutiérrez & Molina, 2023). However, much of this research has been limited to the initial pandemic phase, leaving an open question about the long-term evolution of telework and its broader socioeconomic implications. This study builds upon existing work by utilizing Google Mobility Reports, which provide aggregated and anonymized mobility behavior based on location data from the personal devices of Google users, to analyze how the removal of workplace restrictions influenced telework adoption and mobility trends in European cities.

Based on this approach, our study has two specific objectives. First, to identify the trends in telework and workplace mobility across European cities in recent years, where data is available. Second, to create counterfactuals that allow measurement of the impacts induced by relaxing mandated restrictions on mobility as an instrument for remote work intensity. Our results show a significant association between the relaxation of workplace restrictions and a decrease in workplace mobility. The findings suggest a potential rise in remote work adoption, particularly in larger cities, emphasizing the intricate dynamics of workplace measures and their implications for remote work trends.

This work contributes to the recent literature linking big data with the study of telework, mobility, and labor policy design (Stiles & Smart, 2021; Wöhner, 2022). We extend over the current research by introducing lockdown stringency as exogenous variation on telework, to understand changes in workplace mobility, adjusting for differences in the local economic activity mix. From a policy perspective, the results are critical for several dimensions of the European labor market: telework regulation, workplace health standards, transportation, and urban planning, among others.

Data

Google Mobility Reports

The first source is derived from Google Mobility Reports, data consistently published throughout the pandemic to measure relative variations in individual mobility in response to imposed restrictions. These reports provide insights into changes in the number of visitors, or the time spent in categorized locations compared to reference days, representing the average value during a five-week period from January 3 to February 6, 2020.

The information within Google Mobility Reports stems from aggregated and anonymized data collected from users who have activated location history. This history creates a timeline of an individual's visited locations, routes taken, and journeys. Google calculates the attendance variation in various categories, such as businesses, recreational areas, supermarkets, pharmacies, parks, public transport stations, workplaces, and residential areas.

Google offers mobility reports at different geographical levels. For this study, we focus on obtaining data related to the main subdivisions of selected countries: Spain, Italy, France, and Sweden. It is important to note that subdivisions vary in each country, with data from 51 provinces in Spain, 15 regions in Italy, 21 counties in Sweden and 95 metropolitan departments in France.

The dataset spans daily records from February 15, 2020, to October 15, 2022. The high-frequency nature of the data poses challenges, including missing values due to Google's data quality and privacy thresholds. Additionally, the dataset contains daily values for weekends and holidays. To accurately analyze work mobility, we model the impact of holidays using the Python library Prophet. Prophet is a time series forecasting procedure based on an additive model, incorporating non-linear trends, yearly, weekly, and daily seasonality, and holiday effects. Robust to missing data and trend shifts, Prophet is open-source software developed by Facebook's Core Data Science team.

We apply seasonal decomposition to isolate trend and annual seasonal effects, as illustrated in Figure 1. Weekends are excluded, and we calculate weekly averages by transforming the data from daily to weekly frequency for a comprehensive analysis of work mobility.

In this study, we utilize datasets provided by Eurostat through the Urban Audit project to acquire comprehensive data on European cities. Eurostat's Urban Audit, along with the Large City Audit project, stands out as a valuable resource, providing key insights into the diverse dimensions of urban life across Europe. Data specific to European cities are systematically collected as part of the Urban Audit and the Large City Audit project. These initiatives are dedicated to enhancing urban life quality, fostering exchange of experiences among European cities, identifying best practices, benchmarking at the European level, and offering insights into the dynamic interactions within cities and their surroundings.

City level data

At the city level, the Urban Audit dataset comprises a rich set of indicators and variables, offering a comprehensive view of various aspects of quality of life. These dimensions encompass demography, housing, health, economic activity, labor market dynamics, income disparity, educational qualifications, environmental factors, climate, travel patterns, tourism, and cultural infrastructure. The data collected through the Urban Audit project spans annually, dating back to 1990. These datasets are available for European Union (EU) Member States, the United Kingdom (UK), Iceland, Switzerland, Norway, and Turkey. The inclusion of these countries ensures broad representation and a diverse range of urban settings in the data collection.

Oxford Coronavirus Government Response Tracker Data (OxCGRT)

Additionally, we used time series data obtained from the Oxford Coronavirus Government Response Tracker (OxCGRT), reflecting teleworking policies and recommendations in each of the analyzed countries. In our analysis, we incorporated two key indicators. Firstly, the Stringency Index, a composite measure based on nine response indicators such as school closures, workplace shutdowns, and travel bans, rescaled to a value ranging from 0 to 100, with 100 representing the most stringent measures. Secondly, a variable reflecting the national teleworking status, determined by selecting the strictest values among all regions within a nation for workplace closures:

0: No measures

1: Recommended closure (or work from home)

2: Required closure (or work from home) for some sectors or categories of workers

3: Required closure (or work from home) for all but essential workplaces (e.g., grocery stores, doctors)

As the treatment effect, we considered the national teleworking status, particularly the moment when a country transitions from status 1, 2 or 3 to status 0. This transition signifies the shift from mandatory or recommended work from home practices to no measures of remote working. Thus, by using this categorical variable, we established the time period for analysis. To focus on the impact on working mobility after the removal of workplace restrictions, we selected the period from July 12, 2021, to March 7, 2022. Our final sample comprises 34 weeks during which one country—France—relaxed its work from home policies from level 2 to 0. Consequently, we have multiple treated units, 74 French cities, where the treatment initiates at February, 2022.

Empirical Strategy

To analyze the impact of restrictions on labor mobility, we employ synthetic control methods (Abadie & Gardeazabal, 2003). These methods constitute a generalization of Difference-in-Differences (DID) approaches as they aim to compare a treated group (subject to some form of treatment) with a control group. The objective is to capture the causal effect of the treatment by comparing differences in changes before and after the treatment application between the two groups.

A fundamental assumption for proper identification of the DID method involves the "parallel trends" assumption, stating that, in the absence of treatment, the average outcomes of treated and control units would follow parallel paths. However, in many cases, parallel pretreatment trends are not supported by the data, suggesting that the parallel trends assumption is likely to fail in the posttreatment period. To address this issue, two distinct strategies exist. The first involves synthetic control methods, which aim to balance the influence of potential time-varying confounders between the control group and the treatment group prior to estimation (Abadie, 2005; Abadie, Diamond, and Hainmueller, 2010; 2015).

The second approach to address unobserved heterogeneities that change over time explicitly models these variations. A common strategy is to add unit-specific time trends to conventional two-way fixed effects models. This approach relies on the assumption that treatment assignment is ignorable conditional on both fixed effects and the imposed trends (Mora and Reggio, 2012). However, controlling for these trends can consume many degrees of freedom and may not necessarily solve the problem if the underlying confounders do not conform to the specified trends. An alternative is to adopt a semiparametric approach to model unobserved confounders that vary over time. Bai (2009) proposes an Interactive Fixed Effects (IFE) model incorporating unit-specific intercepts interacted with time-varying coefficients. The IFE model captures how specific factors change over time, providing a nuanced understanding of the temporal dynamics affecting different units. It does so by incorporating unit-specific intercepts representing initial differences between units and coefficients that vary over time, referred to as latent factors. Estimation of the IFE model involves conducting a factor analysis of residuals from a linear model, followed by estimating the final linear model that accounts for the influence of a fixed number of the most influential factors. In summary, the IFE model allows for capturing both the initial differences between units and how these units respond to factors that change over time.

In the literature, methods combining both strategies for proper specification are found. Xu (2017) proposes a Generalized Synthetic Control Method (GSCM) method that links both approaches and unifies the synthetic control method with linear fixed effects models. Initially, an Interactive Fixed Effects (IFE) model is estimated using only control group data, obtaining a fixed number of latent factors. Subsequently, factor loadings for each treated unit are estimated by linearly projecting pretreatment outcomes onto the space defined by these factors. Finally, counterfactuals for treated units are imputed based on the estimated factors and factor loadings.

Following this method, we estimate the following specification:

$$Y_{it} = \delta_{it} D_{it} + x'_{it}\beta + \lambda'_{it} f_t + \alpha_i + \xi_t + \varepsilon_{it},$$

where Y_{it} is the main dependent variable measuring the percentage variation from the baseline period in workplace attendance. D_{it} is a binary variable indicating 1 if unit i has been treated in period t and 0 otherwise. x_{it} represents control variables for each city i during period t, f_t is a vector of unobserved common factors, and ε_{it} is the error term for each city i in period t unrelated to the treatment effect. The accompanying parameters to be estimated are: δ_{it}, the heterogeneous treatment effect for each city i, β is the parameter vector accompanying covariates, and λ_{it} is an unknown vector of factorial loadings. Additionally, we observe α_i and ξ_t, which are additive fixed effects for unit and time, respectively. From the estimation of this model, the average treatment effect on treated units (ATT) can be calculated as:

$$ATT = \frac{1}{N_{tr}} \sum_{i \in N} [Y_{it}(1) - Y_{it}(0)]$$

where $Y_{it}(1)$ is the observed effect after treatment, and N_{tr} is the number of treated units. For model selection, specifically choosing the unobserved factors to include, Xu (2017) establishes a cross-validation algorithm. This procedure uses information from both the control and treatment groups in pre-treatment periods. Essentially, cross-validation is a technique involving splitting the data into training and testing subsets to evaluate the model's performance on unused data during estimation. In this case, information from both the control and treatment groups before treatment is used to select the model that best generalizes to unobserved data. The algorithm then selects the model that, on average, makes the most accurate predictions.

To obtain uncertainty estimates, we use a non-parametric bootstrap process for the Generalized Synthetic Control due to the big size of the treatment group (greater than 40 treated units). In essence, uncertainty estimates conditional on observed covariates and unobserved factors are obtained using a non-parametric bootstrap procedure blocked at the subdivision level of 2000 times through the sampling of residuals. For the estimation method we follow Gobillon & Magnac (2016) proposition of using the EM algorithm which takes advantage of the treatment group information during the pre-treatment period. First, we will estimate our model in the full sample without restricting it to any population size. Secondly, we will run our model on a restricted sample for cities with more than 200,000 inhabitants to account for potential variations in urban dynamics or demographic factors associated with larger population centers.

Results

Table 1 summarizes the results obtained for both the restricted and unrestricted sample. In Column 1 the cross-validation algorithm finds 5 unobserved factors to be important. After including unit and time fixed effects and the unobserved factors found, the estimated ATT based on the GSC method is -6.3% with a standard error of 1.5%. This means that relaxation of the workplace restrictions is associated with a statistically significant decrease in workplace mobility. We find other estimated coefficients for the remaining covariates. The logarithm of national COVID-19 daily cases shows a positive and statistically significant coefficient while sex-ratio (women per 100 males) and residential mobility show negative and statistically significant coefficient estimations. Figure 2 shows the dynamics of the estimated ATT, during the pre-treatment estimated average workplace mobility matches well the actual average workplace mobility. After the treatment effect both series diverge showing lower than expected workplace mobility. In other words, the relaxation of workplace measures did not increase workplace mobility, conversely evidence shows the opposite, which may suggest an increase in the adoption of working from home. Figure 3 shows that the estimates for the average treatment effect and the estimated untreated average both fall within the 95% confidence interval bands for both the treatment and non-treatment groups.

In Column 2, we show the estimated coefficients for the restricted sample for cities with more than 200.000 inhabitants. Therefore, the estimations for greater cities. Cross-validation scheme finds 4 unobserved factors. Including the unobserved factors, fixed effects, and control covariates we find an estimated ATT of -4.9% variation in workplace mobility with an estimated standard error of 0.38%. In comparison with the unrestricted sample, we find a lower estimated ATT in absolute values, which suggests that workplace variation was lower in greater cities. Regarding the control variables, we find the similar effects associated with these variables. The logarithm of national covid-19 cases shows appositive and statistically significant coefficient while the logarithm of the city population, sex-ratio (women per 100 males), the stringency index and residential mobility show negative and statistically significant coefficient estimations. Figures 3 and 4 show the time series of the ATT and the actual workplace mobility series, for the unrestricted and restricted sample, respectively. Again, we find a good match between series in the pre-treatment period while a divergence after the treatment period which falls in between the 5-95% confidence interval for the treated and non-treated.

Conclusion

The COVID-19 pandemic has acted as a catalyst for accelerated technological advancements in various economic sectors, particularly those necessitating adaptation due to containment measures. Concerns have emerged regarding its long-term impact on productivity, encompassing challenges in training, on-the-job learning, creativity, and teamwork. While employees value the flexibility associated with remote work, they also express apprehensions about issues such as isolation, ergonomics, and work-life balance. Additional considerations include presenteeism and the potential exacerbation of social and economic inequality. This study focuses on assessing the impact of the removal of mandated workplace restrictions in 2022 on workplace mobility across French cities from.

To achieve this objective, the study relies on three primary data sources to analyze workplace mobility patterns and the consequences of COVID-19-related restrictions. Google Mobility Reports provide insights into changes in individual mobility by analyzing aggregated and anonymized data from users with activated location history. The dataset spans from February 15, 2020, to October 15, 2022, covering subdivisions in selected European countries. Addressing data challenges, the Python library Prophet is employed for accurate seasonal decomposition, with a focus on work mobility by excluding weekends, bank holidays, and calculating weekly averages. Eurostat's Urban Audit project contributes comprehensive city-level data, spanning various dimensions of urban life across Europe. Data from the Oxford Coronavirus Government Response Tracker (OxCGRT) is used to assess teleworking policies and recommendations, including the Stringency Index and a variable indicating national teleworking status. The treatment effect is determined by transitions in teleworking status, concentrating on the period from July 12, 2021, to March 7, 2022, with 74 French cities serving as multiple treated units during the relaxation of work-from-home policies.

For the impact assessment of COVID-19-related restrictions on labor mobility, generalized synthetic control methods are employed, extending traditional DID approaches. The GSCM method, proposed by Xu (2017), unifies IFE modeling and synthetic control. The results indicate a significant association between the relaxation of workplace restrictions and a decrease in workplace mobility. The estimated ATT reveals a -6.3% reduction, with additional coefficients highlighting associations with national daily COVID-19 cases, city population, sex-ratio, stringency index, and residential mobility. Notably, the post-treatment divergence in workplace mobility suggests a potential increase in remote work adoption. In cities with over 200,000 inhabitants, the estimated ATT is -4.9%, indicating lower workplace variation. Control variables exhibit consistent effects. One limitation of our study is the lack of control over factors related to seasonal employment patterns, which may influence workplace mobility dynamics. Seasonal variations in employment, such as those in industries heavily affected by weather conditions or specific times of the year, could introduce confounding elements not explicitly considered in our analysis. To address this limitation and enhance the robustness of our findings, future research endeavors could explore the inclusion of additional control variables that specifically account for the influence of seasonal employment fluctuations. These findings underscore the nuanced impact of workplace measures on mobility trends and hold implications for understanding the dynamics of remote work adoption.

References

Abadie, A., & Gardeazabal, J. (2003). The economic costs of conflict: A case study of the Basque Country. *American Economic Review, 93*(1), 113–132.

Abadie, A. (2005). Semiparametric difference-in-differences estimators. *The Review of Economic Studies, 72*(1), 1–19.

Abadie, A., Diamond, A., & Hainmueller, J. (2010). Synthetic control methods for comparative case studies: Estimating the effect of California's tobacco control program. *Journal of the American Statistical Association, 105*(490), 493–505.

Abadie, A., Diamond, A., & Hainmueller, J. (2015). Comparative politics and the synthetic control method. *American Journal of Political Science, 59*(2), 495–510.

Andrade, C., Gillen, M., Molina, J. A., & Wilmarth, M. J. (2022). The social and economic impact of COVID-19 on family functioning and well-being: Where do we go from here? *Journal of Family and Economic Issues, 43*, 205–212. https://doi.org/10.1007/s10834-022-09848-x

Bai, J. (2009). Panel data models with interactive fixed effects. *Econometrica, 77*(4), 1229–1279.

Beckel, J. L. O., & Fisher, G. G. (2022). Telework and worker health and well-being: A review and recommendations for research and practice. *International Journal of Environmental Research and Public Health, 19*(7), Article 7. https://doi.org/10.3390/ijerph19073879

Ben-Michael, E., Feller, A., & Rothstein, J. (2021). The augmented synthetic control method. *Journal of the American Statistical Association, 116*(536), 1789–1803.

Buomprisco, G., Ricci, S., Perri, R., & De Sio, S. (2021). Health and telework: New challenges after COVID-19 pandemic. *European Journal of Environment and Public Health, 5*(2), em0073.

Cole, M. A., Elliott, R. J., & Liu, B. (2020). The impact of the Wuhan COVID-19 lockdown on air pollution and health: A machine learning and augmented synthetic control approach. *Environmental and Resource Economics, 76*(4), 553–580.

Criscuolo, C., Gal, P., Leidecker, T., Losma, F., & Nicoletti, G. (2021). The role of telework for productivity during and post-COVID-19: Results from an OECD survey among managers and workers. *OECD iLibrary*. https://www.oecd-ilibrary.org/content/paper/7fe47de2-en

Daneshfar, Z., Asokan-Ajitha, A., Sharma, P., & Malik, A. (2023). Work-from-home (WFH) during COVID-19 pandemic–A netnographic investigation using Twitter data. *Information Technology & People*, *36*(5), 2161-2186.

Dubey, A. D., & Tripathi, S. (2020). Analysing the sentiments towards work-from-home experience during COVID-19 pandemic. *Journal of Innovation Management*, *8*(1), 13-19.

Einav, L., & Levin, J. (2014). Economics in the age of big data. *Science*, *346*(6210), 1243089.

Emanuel, N., & Harrington, E. (2023). Working remotely? Selection, treatment, and the market for remote work. *FRB of New York Staff Report, 1061.* https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4466130

European Commission. (2021). *Tracking EU citizens' concerns using Google search data | Knowledge for policy*. https://knowledge4policy.ec.europa.eu/projects-activities/tracking-eu-citizens%E2%80%99-concerns-using-google-search-data_en

Ferreira, A. I., Mach, M., Martinez, L. F., & Miraglia, M. (2022). Sickness presenteeism in the aftermath of COVID-19: Is presenteeism remote-work behavior the new (ab)normal? *Frontiers in Psychology*, *12*. https://www.frontiersin.org/articles/10.3389/fpsyg.2021.748053

Giménez-Nadal, J. I., Molina, J. A., & Velilla, J. (2020). Work time and well-being for workers at home: Evidence from the American Time Use Survey. *International Journal of Manpower*, *41*(2), 184–206. https://doi.org/10.1108/IJM-04-2018-0134

Giménez-Nadal, J.I., Molina, J.A. & Velilla, J. Work from home, time allocation, and well-being: the impact of lockdowns. *Rev Econ Household* (2024). https://doi.org/10.1007/s11150-024-09744-3

Henke, R. M., Benevent, R., Schulte, P., Rinehart, C., Crighton, K. A., & Corcoran, M. (2016). The effects of telecommuting intensity on employee health. *American Journal of Health Promotion*, *30*(8), 604–612. https://doi.org/10.4278/ajhp.141027-QUAN-544

López Soler, J. R., Christidis, P., & Vassallo, J. M. (2023). Evolution of teleworking and urban mobility changes driven by the COVID-19 pandemic across European cities. *Transportation Research Procedia*, *69*, 488–495. https://doi.org/10.1016/j.trpro.2023.02.199

Milasi, S., González-Vázquez, I., & Fernández-Macías, E. (2021). Telework before the COVID-19 pandemic: Trends and drivers of differences across the EU.

Molina, J. A., & Gutiérrez, A. (2023). Teletrabajo y movilidad: Una aplicación socioeconómica de la inteligencia artificial. In *Inteligencia Artificial y Sistemas Autónomos Cognitivos - UNIDIGITAL IASAC* (Ed. Francisco Serón). Plan de Recuperación, Transformación y Resiliencia, Ministerio de Universidades y Unión Europea. http://unidigitaliasac.unizar.es/ficha/teletrabajo-y-movilidad-una-aplicacion-socioeconomica-de-la-inteligencia-artificial

Renu, N. (2021). Technological advancement in the era of COVID-19. *SAGE Open Medicine*, *9*, 20503121211000912. https://doi.org/10.1177/20503121211000912

Saura, J. R., Ribeiro-Soriano, D., & Saldaña, P. Z. (2022). Exploring the challenges of remote work on Twitter users' sentiments: From digital technology development to a post-pandemic era. *Journal of Business Research*, *142*, 242-254.

Stiles, J., & Smart, M. J. (2021). Working at home and elsewhere: Daily work location, telework, and travel among United States knowledge workers. *Transportation*, *48*(5), 2461–2491. https://doi.org/10.1007/s11116-020-10136-6

Wöhner, F. (2022). Work flexibly, travel less? The impact of telework and flextime on mobility behavior in Switzerland. *Journal of Transport Geography*, *102*, 103390. https://doi.org/10.1016/j.jtrangeo.2022.103390

Zalat, M., & Bolbol, S. (2022). Telework benefits and associated health problems during the long COVID-19 era. *Work*, *71*(2), 371–378. https://doi.org/10.3233/WOR-210691

Zhang, C., Yu, M. C., & Marin, S. (2021). Exploring public sentiment on enforced remote work during COVID-19. *Journal of Applied Psychology*, *106*(6), 797.

Figure 1. Google mobility reports series vs processed data.

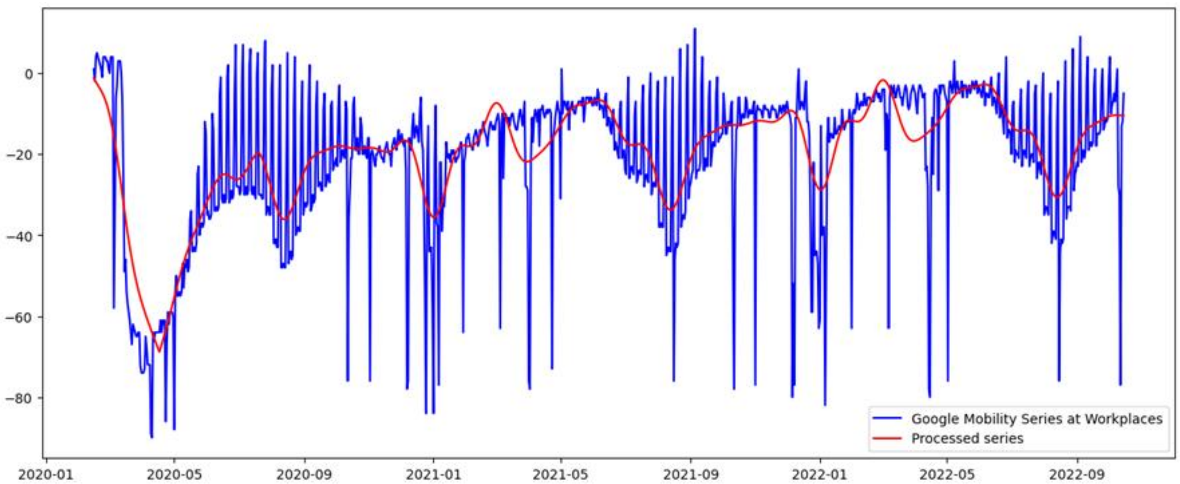
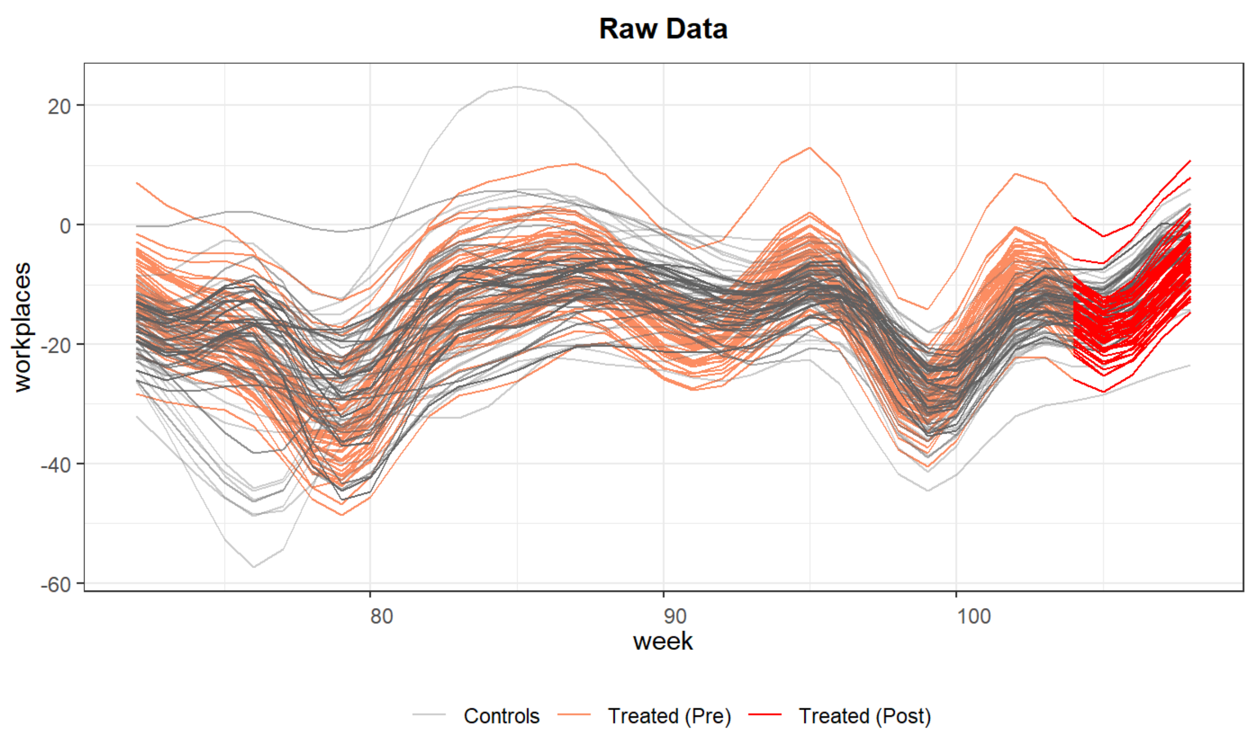


Figure 2. Workplace mobility during sample period



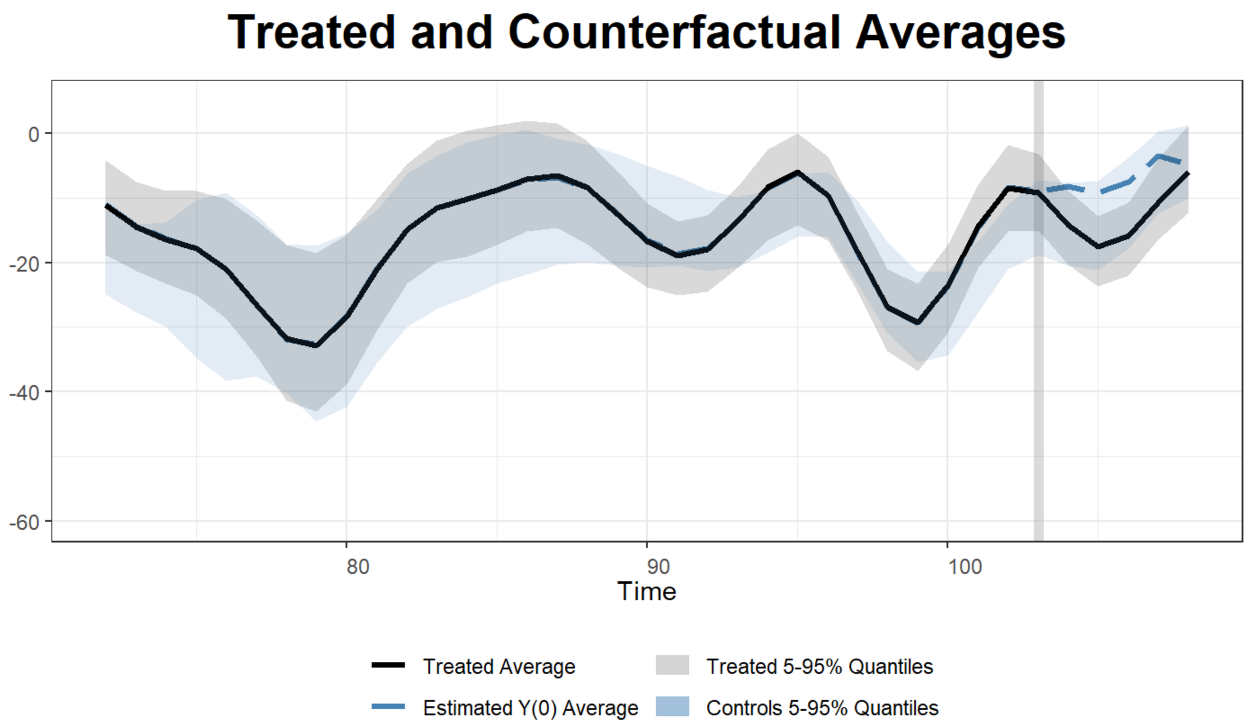
Note: Figure shows workplace mobility for the cities under consideration throughout the sample period of analysis, spanning from July 12, 2021, to March 7, 2022. The graph illustrates both treated and untreated units.

Table 1. GSCM results for restricted and unrestricted samples

Outcome variable	Unrestricted sample (1)	Restricted sample (2)
ATT	-6.277***	-4.945***
	(-1.544)	(0.385)
Daily covid-19 cases	0.000*	0.000***
	(0.000)	(0.000)
Population	-0.131	-0.099***
	(0.085)	(0.002)
Sex ratio	-2.641***	-2.307***
	(0.586)	(0.286)
Stringency index	0.021	0.022**
	(0.017)	(0.008)
Residential mobility	-0.937***	-1.242***
	(0.121)	(0.030)
Unit fixed effets	YES	YES
Time fixed effects	YES	YES
Unobserved factors	5	4
Observations	13,838	3,708
Treated cities	74	24
Control cities	300	77

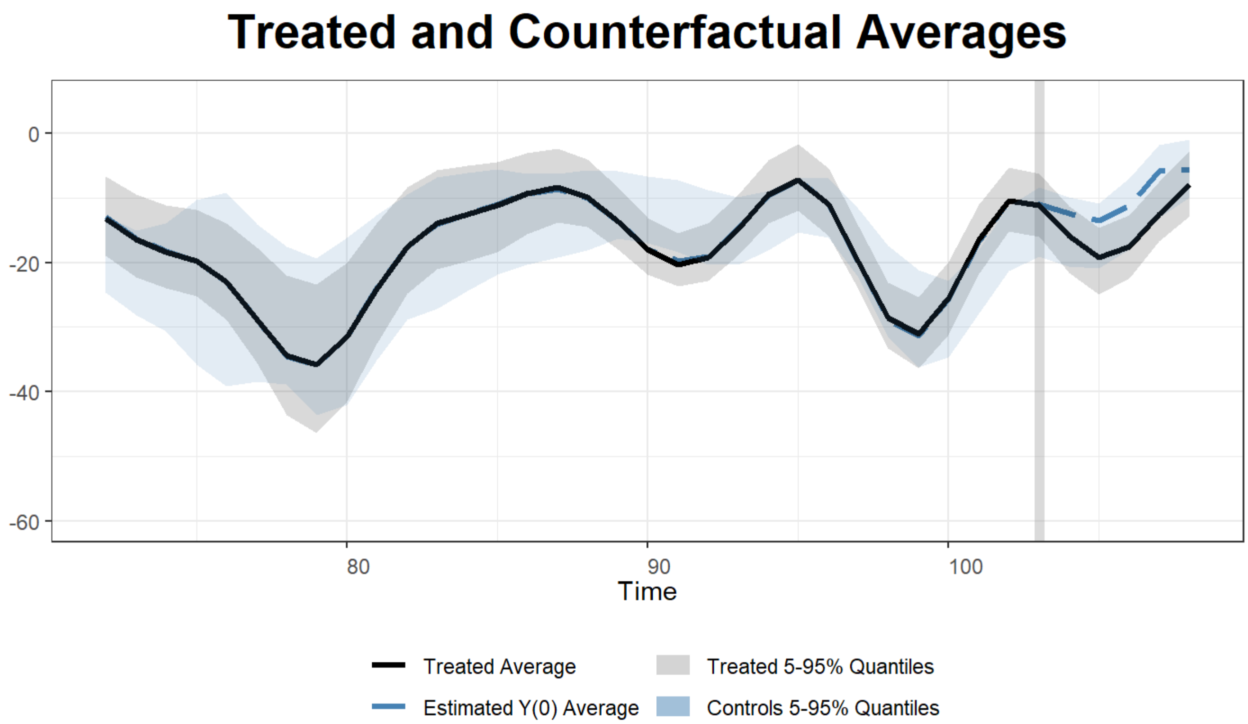
Note: Standard errors in column (1) is based on nonparametric bootstrap (blocked at the subnational level) of 2,000 times. Standard errors in columns (2) is based on parametric bootstrap (blocked at the subnational level) of 2,000 times.

<u>Figure 3. Treated and Counterfactual Averages for unrestricted sample</u>



Note: The figure displays treated and counterfactual average estimates for the Generalized Synthetic Control Method (GSCM) in our unrestricted sample.

<u>Figure 4. Treated and Counterfactual Averages for restricted sample</u>



Note: The figure displays the treated and counterfactual average estimates for the Generalized Synthetic Control Method (GSCM) in our restricted sample, limited to cities with more than 200,000 inhabitants.