Zero fare, cleaner air? The causal effect of Luxembourg's free public transportation policy on carbon emissions

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Abstract

In March 2020, Luxembourg became the first country in the world to offer free public transport across all modes of transport. We leverage this unique quasi-experimental setting to evaluate whether Luxembourg's free public transport policy has induced a shift from private motorized transport to free public transport. To assess this shift, we measure the reduction in carbon emissions from road transport as an indicator of reduced dependence on private motorized vehicles. We use spatial panel data from the European Emission Database on Global Atmospheric Research (EDGAR) and utilize the recently proposed Synthetic Difference-in-Differences method that combines the advantages of the canonical Difference-in-Difference and Synthetic Control approaches. The study estimates a 6.9% reduction in road transport emissions as a result of the policy, indicating a significant modal shift from private vehicles to public transport. We carefully consider Luxembourg's distinctive characteristics and account for the concurrent COVID-19 pandemic to address potential challenges associated with identification. In particular, we control for confounding factors such as COVID-related restrictions and fuel prices as well as changes in commuting and working-from-home. Event study analyses and sensitivity checks indicate the overall robustness of our results.

Keywords: Transportation, Emissions, Public Transport, Synthetic DiD

JEL Codes: C21, C33, Q54, R48

1 Introduction

The transport sector is a significant source of greenhouse gas (GHG) emissions. In 2019, it is estimated to be responsible for almost 15% of global net anthropogenic GHG emissions (IPCC, 2022). About a quarter of the European Unions (EU) GHG emissions in 2019 came from the transport sector, of which road transport accounted for about 72% (EEA, 2022). Moreover, GHG emissions from the EU transport sector increased by about 33.5% from 1990 to 2019 (EEA, 2022). This stands in contrast to all other sectors, which experienced a decrease in emissions over the same period (Crippa, Guizzardi, Banja, et al., 2022). Therefore, reducing emissions from the transport sector is imperative to mitigate the negative impacts of climate change and limit further warming of the planet. Additionally, reducing transport sector emissions is critical for the EU to achieve its goal of climate neutrality by 2050 (EEA, 2022).

The provision of affordable and efficient public transport is often discussed as an effective way of reducing carbon (CO2) emissions from the transport sector (Federal Transit Administration, 2010; International Transport Forum, 2020). Accessible, affordable, and efficient public transport can encourage a shift from private motorized transport to the more environmentally friendly public transport. Such shifts can help reduce emissions from the transport sector. In March 2020, Luxembourg became the first country in the world to offer free public transport on all modes of transport (buses, trains, and trams) throughout the country (Research Luxembourg, 2021). This policy initiative created a unique quasi-experiment to examine the effectiveness of free public transport in curtailing emissions in the transport sector. Our paper exploits this quasi-experimental setting created by this policy intervention to quantify its effect on CO2 emissions in Luxembourg's road transport sector.

Our paper links to a large body of literature that ex-post evaluates transport policies designed to decrease reliance on motorized vehicles. Policies aimed at mitigating transport emissions can be categorized into three main strategies. The first category examines policies intended to directly reduce or restrict the use of motor vehicles by making driving more costly or less convenient. These include initiatives such as low-emission zones (Sarmiento et al., 2023; Wolff, 2014), driving restrictions (Davis, 2008, 2017; Gallego et al., 2013), and tax-based instruments (Andersson, 2019; Pretis, 2022). The second category includes policies encouraging a shift towards more sustainable modes of transport, in particular by subsidizing public transport systems (Aydin & Kürschner Rauck, 2023; Borsati et al., 2023; Gohl & Schrauth, 2024) or improving public transit infrastructure (Chen & Whalley, 2012; Gendron-Carrier et al., 2022; Lalive et al., 2018; Li et al., 2019). Policies in the third category aim to improve the energy and fuel efficiency of vehicles through regulations such as gasoline content standards (Auffhammer & Kellogg, 2011). While most studies focus on individual policies, some jointly examine multiple interventions (Eibinger et al., 2024; Koch et al., 2022; Kuss & Nicholas, 2022; Winkler et al., 2023).

Literature on public transport provision and improvements is particularly relevant for the context of this contribution. Research examining the impact of enhancing public transportation generally reports a decrease in air pollution. Li et al. (2019) assess the effect of subway expansion on air quality in China, while Lalive et al. (2018) investigate the impact of increased regional rail service in Germany. Additionally, Chen and Whalley (2012) explore the consequences of introducing a new rail transit system in Taipei. All these studies conclude that such policies lead to an improvement in air quality, effectively reducing air pollution. Gendron-Carrier et al. (2022) examine the effect of opening subway systems on air pollution in 58 cities, and despite observing no average effect, they identify a decrease in air pollution specifically in cities that initially had higher levels of pollution.

Studies investigating the effects of fare decreases generally report a decrease in air pollution. For instance, research by Aydin and Kürschner Rauck (2023) and Gohl and Schrauth (2024) examine the impact of the 9-Euro ticket introduced in Germany in 2022 on air quality. Both studies observed a decline in air pollution following the introduction of the 9-euro ticket, with more significant reductions noted in regions well-served by public transit systems. In contrast, Borsati et al. (2023) investigate the effects of a four-month public transport subsidy implemented in Spain in 2022 but finds no significant evidence of improved air quality.

However, literature on the effects of free public transport is still scarce. We know of only a few studies on the effects of free public transport within cities. Tallin (Estonia) introduced free public transit in 2013. Descriptive work by Cats et al. (2017) found that this policy lead to an increase in public transport usage, but had no significant effect on car usage. Bull et al. (2021) randomly assigned free public transport vouchers to workers in Santiago (Chile). These were mainly used during off-peak hours, suggesting an increase in the use of public transport for leisure activities rather than a reduction in car use. Tomeš et al. (2022) study two massive long-distance fare discount schemes for children, students, and pensioners in Slovakia and Czechia. The former introduced free railway fares for these groups from 2014 on, while the latter introduced a 75% discount for trains and busses from 2018 on. They found a significant increase in public transport usage for these groups, but do not discuss changes in car usage.

Our study contributes to the existing literature by analyzing the causal impact of Luxembourg's free public transport policy, launched in March 2020, on the country's road transport CO2 emissions. Luxembourg's position as the first country in the world to implement this policy provides a unique experimental context. The existence of a large number of countries and regions without free public transport provides an opportunity to construct a counterfactual scenario. This scenario would represent a suitable comparison for the trajectory of Luxembourg's road transport CO2 emissions if the policy had not been implemented. This allows us to evaluate the causal impact of this policy on road transport CO2 emissions. To the best of our knowledge, our study is the first to empirically assess the direct causal effect of free public transportation on CO2 emissions. The results of our study thus provide a unique and significant contribution to the body of evidence regarding the efficacy of public transportation as a strategy to tackle climate change.

We use the recently proposed SDID method and construct a counterfactual CO2 emission trajectory for Luxembourg from a pool of donor regions consisting of all other European countries at the Nomenclature for Territorial Units for Statistics (NUTS) 2 regional level. We conduct our analysis at the NUTS 2 level, as Luxembourg itself constitutes a NUTS 2 region. Moreover, Luxembourg is quite different to other European countries in economic terms and NUTS 2 regions can offer a more suitable comparison to Luxembourg in terms of their emission trajectories compared to entire countries. We further include covariates to control for the potential confounding effects arising from the COVID-19 pandemic, the resulting changes in commuting, working-from-home patterns, and changes in fuel prices that could also affect road transport CO2 emissions.

We estimate that the free public transport policy in Luxembourg led to an estimated average treatment effect (ATT) of around 6.9% reduction in CO2 emissions from the road transport sector. To the best of our knowledge, there is only one other study that directly looks at Luxembourg free public transportation policy. Bigi et al. (2023) use an agent-based modelling approach to show that the policy significantly contributed to a modal shift from private vehicles to public transport, but that it did not significantly impact congestion levels. Our results are in line with their findings and appear robust across different specifications.

The rest of the paper is organized as follows. Section 2 briefly introduces Luxembourg's free public transit policy. Data and the identification strategy are discussed in Section 3. The empirical strategy, including the SDID procedure, is detailed in Section 4. Section 5 provides our empirical results and robustness tests. The results and potential mechanisms are discussed in Section 6. Finally, Section 7 provides concluding remarks.

2 The policy

On March 1, 2020, Luxembourg became the first country in the world to offer free public transport nationwide, available to all residents and visitors.[1] This initiative was part of the broader mobility strategy, "Modu.2.0" aimed at improving the sustainability of the mobility system (Ministère du Développement Durable et des Infrastructures, 2018). With the highest car density in Europe and facing significant congestion problems, Luxembourg designed this policy not only to alleviate traffic but also to support social equity by making travel more accessible for low-income earners. The initiative thus underscores a commitment to sustainable mobility and inclusivity. Before the implementation of this policy annual revenue for ticket sales in Luxembourg amounted to about 41 million euros, which was approximately 8% of the annual cost of maintaining the transport system. Financing for the free public transit policy now comes from taxpayers.

The existing public transportation infrastructure comprises buses, trams, and trains. It forms the backbone of this initiative and provides wide accessibility and efficient service across the country. Buses are the predominant mode of public transportation in Luxembourg, offering comprehensive coverage across the entire country. These connect different localities as well as cross-border lines (Ministère du Développement Durable et des Infrastructures, 2020). Altogether about 400 bus lines are running through Luxembourg, connecting the entire country (Administration des transports publics, 2024). The city of

[1] Tickets are only required for 1st class travel

Luxembourg is additionally served by the only tram line in the country, covering around 10km through 17 stations (Département de la mobilité et des transports, 2024). Trains additionally cover the country in a star-like network, with its center in Luxembourg city (Département de la mobilité et des transports, 2020).

It is worth noting that the free public transit policy was complemented by enhancements in the transportation infrastructure, notably through the strategic expansion of the national rail network's capacity. In 2017, Luxembourg introduced a tram line traversing Luxembourg City, initially connecting 8 stations. The following year saw the line's expansion, adding 3 more stops. December 2020 marked another significant extension, enlarging the network by 2 kilometers and incorporating 4 additional stations. By September 2022, the tram network further expanded with the addition of 2 new stations. The latter two expansions took place after the free public transportation policy was introduced. Currently, the tram stretches over 10 kilometers, serving 17 stations, and includes 6 major interchanges (Département de la mobilité et des transports, 2024). Luxembourg plans to further introduce 3 more tramlines by the end of 2035 (Luxtoday, 2022).

With a substantial number of cross-border commuters, Luxembourg has focused on improving parking availability, particularly near border areas. Additionally, through negotiations with neighboring transport networks, fares for cross-border transport have been lowered (Ministry of Mobility and Public Works, 2020). As a result, the new scheme is designed to benefit not only residents but also those commuting from neighboring countries. The strategic objective for 2025 is to reduce congestion during peak hours while transporting 20% more people than in 2017.

3 Data and identification

Causal policy evaluation studies face a fundamental problem arising from the inability to directly observe potential outcomes of a specific unit both in the presence and in the absence of a policy event (treatment). This makes it difficult to establish causal relationships, as it is not possible to observe the treated unit in its untreated state following a policy intervention. In the case of Luxembourg, this translates to "what would the CO2 emissions from the road transport sector have been if the free public transport policy was not introduced?" To overcome this problem, it is necessary to identify an appropriate identification strategy that allows the construction of a credible comparison group that can be used as a counterfactual for Luxembourg after the introduction of the policy.

In our specific setting, we face two main challenges when selecting an appropriate identification strategy. First, Luxembourg differs from other European countries in many ways. It is a small country, measuring around 2,586 km^2. In the NUTS statistical region, it is a single region at all levels. Its population is also relatively small at around 660,000. Conversely, GDP per capita at around 140,000 USD is also highest among all EU countries. Moreover, CO2 emissions from transport per capita are highest among all EU member states at around 8,200 kg. Luxembourg has the highest car density within the EU at around 700 cars per 1,000 inhabitants. To identify the effect of free public transport, we want to compare the evolution of transport emissions with comparable regions in terms of their emission trajectories. The uniqueness of Luxembourg therefore makes it difficult to find a suitable counterfactual. It would be difficult to meet the parallel trend assumption necessary to conduct a difference-in-difference (DID) estimation, as it is extremely difficult to find a comparable unit based on both observable and unobservable characteristics. This could be compensated for by synthetic control (SC) approaches, which reweight units to adjust for pre-treatment trends (Abadie, 2021). However, this approach also faces difficulties due to the lack of directly comparable regions (not only in their trajectories but in absolute levels) to include in the donor pool to create the synthetic counterfactual, for the reasons discussed above.

To overcome the first challenge, we employ a recently proposed estimation procedure, the SDID approach introduced by Arkhangelsky et al. (2021). SDID combines the strengths of both Difference-in-Differences (DID) and Synthetic control (SC) methods. SDID circumvents the common drawbacks associated with traditional DID and SC methods. Specifically, it overcomes the challenge of estimating causal relationships when parallel trends are not observed in aggregate data for DID and eliminates the necessity for the treated unit to be within the ”convex hull” of control units for SC. Furthermore, given the size of Luxembourg, we carry out the SDID analysis at the NUTS2 regional level to find more comparable control regions. This will be discussed in more detail in Section 4.

Identification is further threatened by variations in mobility patterns unrelated to the free-public-transport policy. Potential confounding includes variation related to the

COVID-19 pandemic, including policy responses to the pandemic, changes in working from home, and changes in commuting. We account for these potential confounders by including covariates to control for these confounding effects in the SDID estimation, which is discussed in more detail in Section 3.1, 3.2 and 3.3. In these sections, we further discuss in detail and provide descriptive statistics of the evolution of transport-related CO2 emissions as well as potential confounders. A detailed description of all variables that we use for analyses is given in Table A.1.

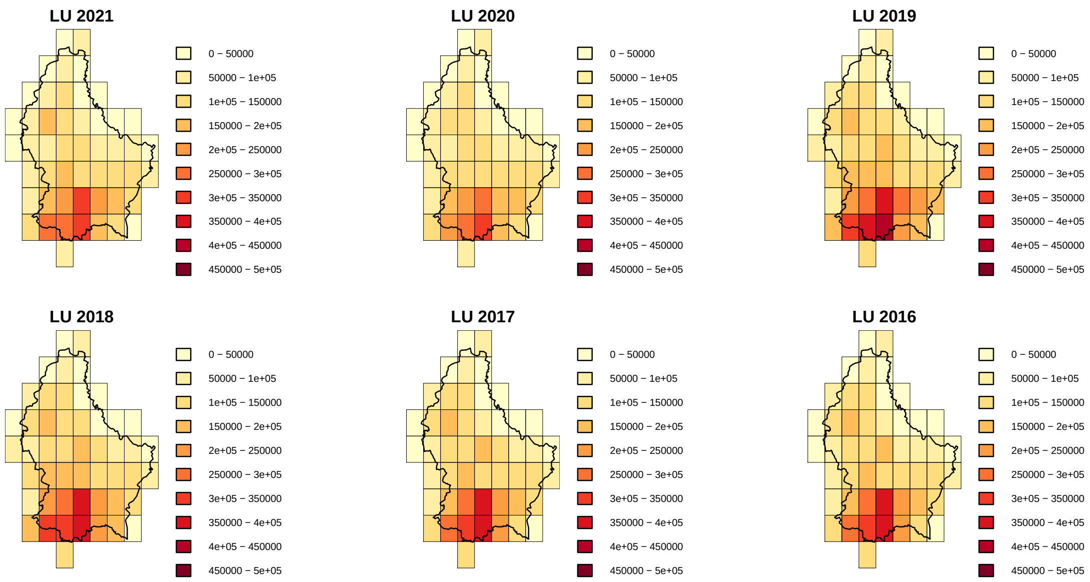
Finally, to avoid bad comparisons with already treated units, we exclude regions from our sample that implemented policies that substantially reduced costs and/or increased accessibility of public transport usage in our sample period. We drop Austria and Estonia from our sample. Estonia introduced free public transport in Tallin in 2013 and extended it since. Given that Estonia is in itself a NUTS 2 region, therefore we drop the whole country. Austria introduced a nationwide climate ticket for all public transport modes in 2021. This increased accessibility and significantly reduced prices for comparable tickets prior to the policy introduction. We also exclude other regions that introduced free or subsidized public transport during the sample period. These regions include Cascais in Portugal, Torrevieja in Spain, Livingo in Italy, Attica in Greece, and Calais, Dunkirk, Nantes, Strasbourg, and Paris in France. We also exclude the NUTS 2 regions surrounding Luxembourg to control for possible spillover effects. These regions include the Province of Luxembourg, and the Province of Liege in Belgium, Trier, and Saarland in Germany, and Lorraine in France.

3.1 Road transport CO2 emissions

Road transport CO2 emissions are extracted from the European Emission Database for Global Atmospheric Research (EDGAR) v8 (Crippa, Guizzardi, Solazzo, et al., 2022). Road transport emissions are categorized as IPCC-1996 sector category 1.A.3.b. Emissions are calculated as the product of fuel consumption times the associated IPCC emission factors. The EDGAR database provides annual sector-specific grid maps expressed in ton substance with a spatial resolution of 0.1 degrees $\times$ 0.1 degrees. We aggregate these grid cells to the corresponding NUTS 2 regions for the following 32 countries located in Europe: Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Liechtenstein, Lithuania, Luxembourg, Malta, Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland, and United Kingdom. The NUTS 2 regional borders are extracted from the Eurostat database (European Commission, 2022).

We present the spatial road transport CO2 emissions for Luxembourg from 2016-2021 in Figure 1.[2] High emissions are indicated in red and lower emissions in yellow. Emissions are concentrated around Luxembourg city and border regions with France. The impact of COVID-19 can be seen in a drop in emissions from 2019 to 2020. Emissions in 2021 and 2022 stay consistently below pre-pandemic values. The reduction in CO2 emissions is directly related to a reduction in fuel consumption, i.e., a shift in mobility patterns. This shift may be attributed to various factors. We are interested in the effect of free public transport, which is one potential source. Another likely source for the variation in CO2 emissions is an increase in the number people working from home and fewer commuting trips.

Figure 1: CO2 emissions from road transport for Luxembourg, 2016-2021



Note: Road transport CO2 emissions are extracted from the European Emission Database for Global Atmospheric Research (EDGAR) v8. Grid cells are 0.1x0.1 degrees. Emissions are expressed in ton substance.

[2]Grid-cells that intersect with the NUTS2 boundaries of Luxembourg are allocated according to their fraction that falls inside these boundaries.

3.2 COVID-19 cases

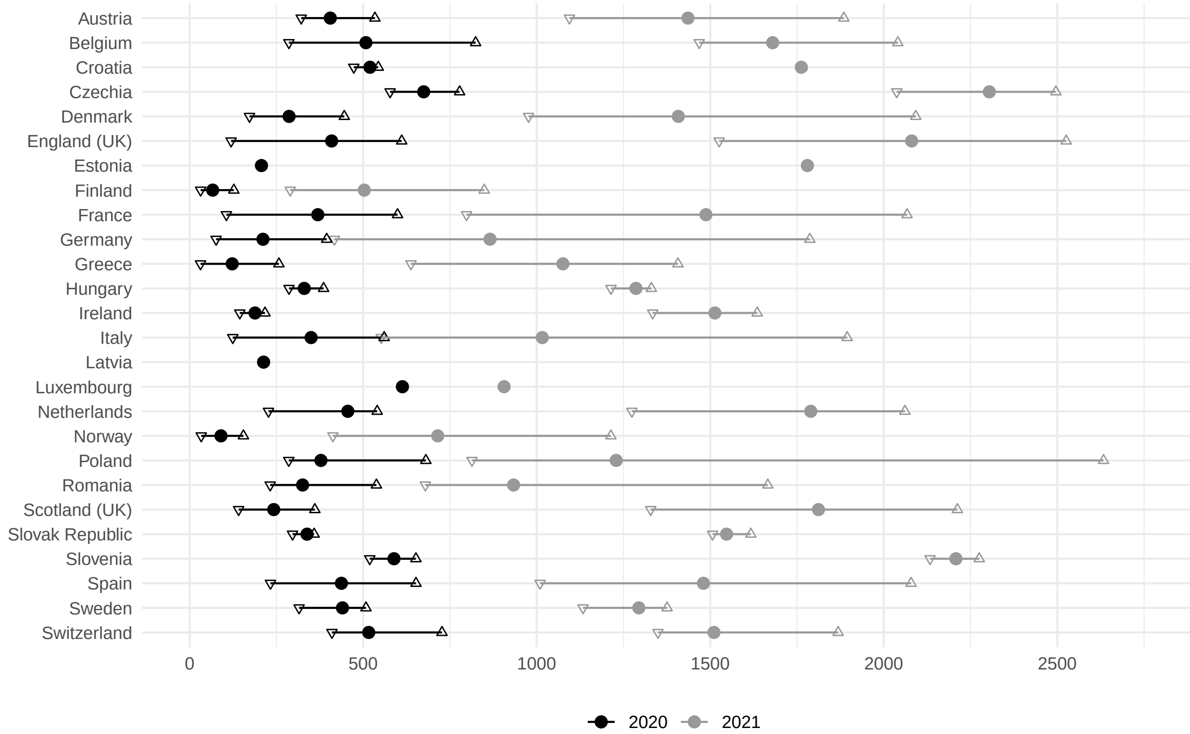
The COVID-19 pandemic is a potential source of variation in mobility patterns unrelated to the free-public-transport policy in Luxembourg. A higher number of COVID-19 cases may, for example, lead to a shift in remote working, online education, and consumer behavior. Additionally, policy responses to the pandemic are potentially influenced by the number of cases and regional mobility restrictions may thus correlated with the number of cases. To accommodate such factors, we explore regional data on daily COVID-19 cases across countries.

Data on confirmed COVID-19 cases are collected and reported by Naqvi (2021) up to the NUTS 3 level. Information on the number of confirmed cases is taken at a NUTS 3 level from each country's official institutions responsible for providing COVID-related data. The regional data is then aggregated up to the country level and cross-checked against data from Our Wold in Data (OWID), which provides confirmed COVID-19 cases at the country level (Mathieu et al., 2020). The data matches well for 2020 and 2021. Data quality, however, deteriorates in 2022, because the number of countries regularly reporting cases decreases strongly in 2022. Naqvi (2021) reports cases for all regions that we consider in our study, except for Luxembourg. However, since the regional data is validated against the OWID data and matches well for our sample-period, we resort to COVID-19 cases from OWID for Luxembourg. For our analysis we aggregate the NUTS 3 level data to the NUTS 2 level.

Figure 2 shows the regional variation in the number of confirmed daily COVID-19 cases per 10,000 population for 2020 and 2021. Dots represent the mean of confirmed cases at the NUTS 0 level (i.e., country level), the downward-facing triangle represents the NUTS 2 region with the lowest and the upward-facing triangle the region with the highest number of confirmed cases per 10,000 persons within a country. The distance between these two points spans the spatial variation across NUTS 2 regions within a country. It is evident that this spatial variation is significant, which further motivates the choice to conduct our study at a regional level compared to the country level.

Overall, the number of cases per 10,000 persons as well as their spatial variation is smaller in 2020 compared to 2021. Countries with a larger population also tend to show a bigger variation in cases across their regions. Luxembourg does not show any regional variation because its NUTS 0 and NUTS 2 regional boundaries are identical. Daily cases

Figure 2: Regional variation in COVID-19 cases for 2020 and 2021



Note: Confirmed COVID-19 cases and their spatial distribution across countries for 2020 and 2021. Data for Luxembourg is from Our Wold in Data (OWID), while data for NUTS2 regions in other countries is taken from Naqvi (2021).

per 10,000 persons for Luxembourg in 2020 and 2021 are around 600 and 900, respectively. In 2020, this puts Luxembourg at the higher end of the spectrum of regional cases per 10,000 persons, while it puts it on the lower end in 2021.

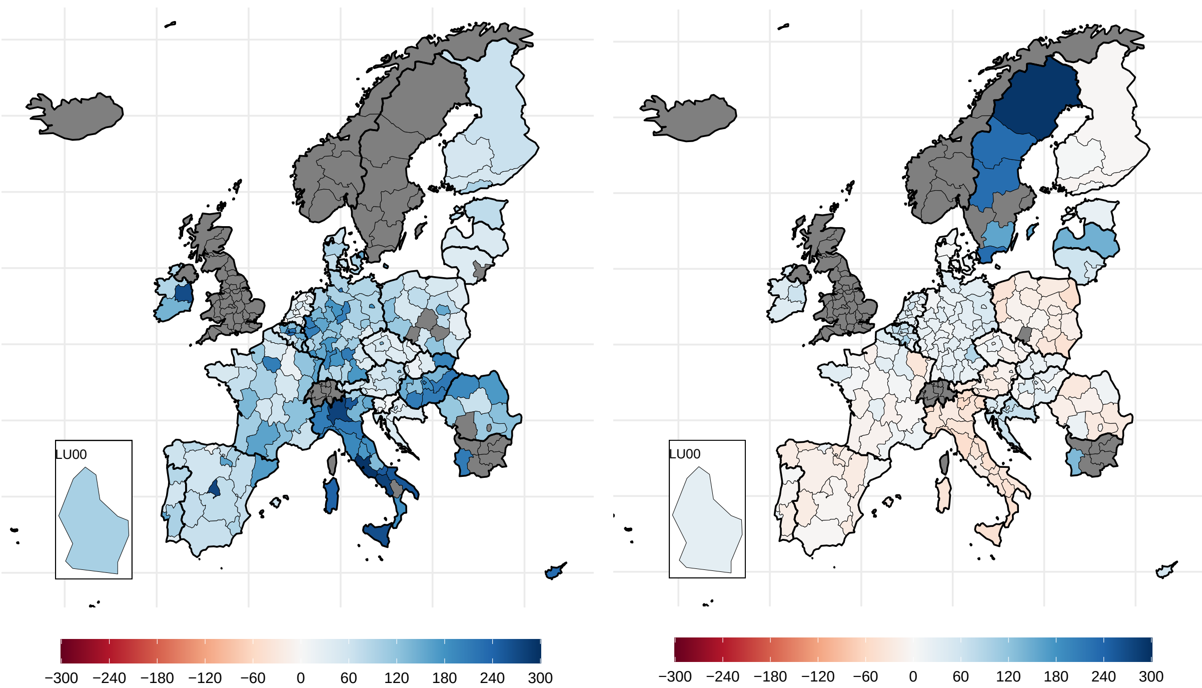
3.3 Working from home and commuting

A main threat to identification are people who changed their mobility pattern with respect to work. This includes persons that did not work at home prior to the pandemic, but started and continued working from home since the COVID-19 outbreak. As a consequence, mobility patterns within a country as well as commuting patterns across countries might have changed. This is problematic for identification when such changes are very different in Luxembourg compared to other regions. Luxembourg experiences a large inflow of commuters relative to their workforce. Around 200,000 persons commute to Luxembourg across the border, which relates to around 44% of its labor force in 2020 (Luxembourg.lu, 2024). Cross-border commuters work in Luxembourg but their residence is located in France, Belgium, or Germany. To study changes in this behavior, we draw on data on working from home and commuting inflow.

Data on working from home is obtained from a special extraction from the EU Labor Force Survey (EU-LFS) for the period 2016-2021. A person is classified as usually working from when they were working at home half of the days that they worked in a reference period of four weeks preceding the end of the reference week in the survey. We focus on persons usually working at home with their workplace location in the associated NUTS 2 region and their location of residence within the same country.[3] However, this dataset does not capture commuting patterns across regions, which seems particularly important for Luxembourg, which traditionally experiences a large commuting inflow. To get a more complete picture of changes in mobility behavior with respect to work, we consider persons never working from home at a regional level. This category captures all persons commuting to work irrespective of their location of residence and thus incorporates commuting inflow from other regions and countries.

Figure 3: Change (%) in persons usually working from home for NUTS2 regions

(a) 2019-2020 **(b)** 2020-2021



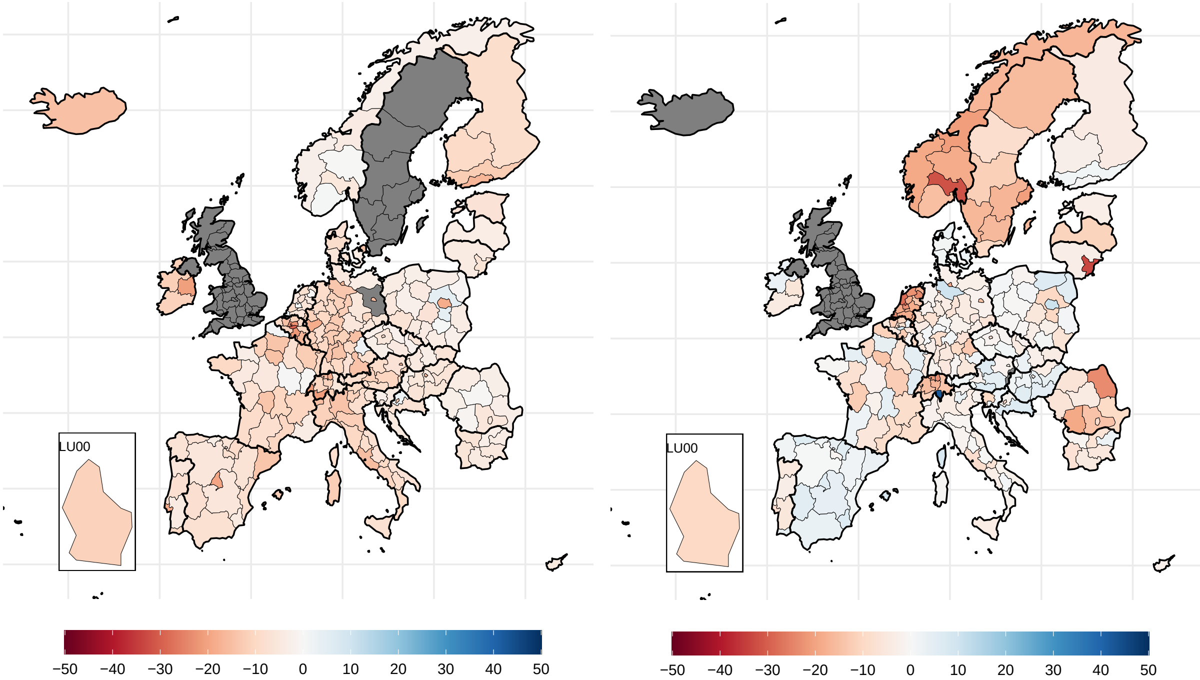
Note: Data is from a special extraction from the EU-LFS. Persons usually working from home with workplace at the NUTS2 region shown in the figure and their location of residence in the associated country of the region.

Figure 3 shows yearly changes of persons usually working from home for NUTS 2

[3]Ideally, we would want to focus on persons working and living in the same NUTS 2 region. However, this would severely limit the data size and is not available from an EU-LFS data structure.

Figure 4: Change (%) of persons never working from home for NUTS2 regions

(a) 2019-2020 **(b)** 2020-2021



Note: Data is from a special extraction from the EU-LFS. The figure shows yearly changes of persons never working at home for NUTS2 regions which are the location of the workplace of these persons irrespective of their location of residence.

regions. Figure 3a shows the change from 2019-2020, i.e., the immediate effect of the pandemic. Blue indicates an increase in working from home, whereas red indicates a decrease. As expected, almost all regions experienced an increase in people working from home. The figure zooms in on Luxembourg, which also experienced an increase, but notice that the change is not particularly strong relative to other regions, i.e., Luxembourg is not an outlier. In Luxembourg, the change of people usually working from home from 2019-2020 almost doubled at around +98%. Figure 3b shows the change from 2020-2021. The map now shows a more nuanced picture. Some regions experienced a decrease in working from home, while some experienced another increase. Luxembourg is among the latter group and experienced a change of around +28%.

Figure 4 shows yearly changes of persons never working at home for NUTS 2 regions. Figure 4a shows percentage changes from 2020 to 2021. Overall, the map shows a decrease in persons never working from home. This is to be expected since the pandemic caused an increase in working from home in most regions. Figure 4b shows percentage changes from 2020-2021 and shows a mixed picture. Some regions experienced a further decrease in persons never working from home, while others experienced an increase following the first year of the pandemic. Luxembourg experienced a decrease in 2019-2020 and 2020-2021 of -12% and -10%, respectively. Again, Luxembourg does not appear to have experienced a particularly strong change relative to other countries.

Both changes in working from home within a region depicted in Figure 3 as well as in never working from home, i.e., commuting inflow, shown in Figure 4 indicate that Luxembourg did not experience particularly strong changes relative to other regions. This mitigates the associated threat to identification. It is nonetheless essential to control for these changes in the empirical analysis. In doing so, we note that the two measures are likely to share a substantial amount of similar information. If the share of people usually working from home increases, it seems likely that the number of persons never working from home decreases. The most significant difference between the measures is that the latter captures changes in commuting inflow from other regions to Luxembourg. We will therefore analyse the impact of these two measurements in the Section 5.1 separately.

4 Empirical strategy

In this section, we provide a brief outline of the synthetic difference-in-differences (SDID) methodology. We compare it to standard difference-in-differences (DID) and standard synthetic control (SC) methods. Then, we go on to explain how covariates are handled in this approach, which is an important aspect of our analysis. Finally, we discuss inference and the extension to an event-study type analysis.

4.1 Synthetic difference-in-differences (SDID)

We use the SDID methodology to assess the impact of Luxembourg's free public transport policy on CO2 emissions from road transport. The analysis covers a sample period from 2016 to 2021. As the policy is implemented in 2020, the analysis includes four years before the policy is introduced and two years after, which allows for a comparative analysis of the pre-and post-policy effects.

The SDID estimator aims to consistently estimate an average treatment effect on the treated (ATT) without relying on parallel pre-treatment trends between treated and every not-treated unit. The ATT is estimated by:

$$\left(\widehat{\tau}^{sdid}, \widehat{\mu}, \widehat{\alpha}, \widehat{\beta}\right) = \underset{\tau,\mu,\alpha,\beta}{\arg\min} \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T} (Y_{it} - \mu - \alpha_i - \beta_t - W_{it}\tau)^2 \widehat{\omega}_i^{sdid} \widehat{\lambda}_t^{sdid} \right\}, \qquad (1)$$

where the outcome of interest, Y_{it} is observed for each unit i at each time t, with $i = 1, ..., N$ and $t = 1, ..., T$. W_{it} indicates treatment, with $W_{it} = 1$ if unit i is treated at time t and $W_{it} = 0$ else. μ is an intercept, α_i and β_t are unit and time fixed-effects, respectively. $\widehat{\omega}_i^{sdid}$ and $\widehat{\lambda}_t^{sdid}$ are unit and time weights, respectively.

Unit weights are computed to align pre-treatments trends between treated and control units:

$$\left(\widehat{\omega}_0, \widehat{\omega}^{sdid}\right) = \underset{\omega_0 \in \mathbb{R}, \omega \in \Omega}{\arg\min} \sum_{t=1}^{T_{pre}} \left(\omega_0 + \sum_{i=1}^{N_{co}} \omega_i Y_{it} - \frac{1}{N_{tr}} \sum_{i=N_{co}+1}^{N} Y_{it} \right)^2 + \zeta^2 T_{pre} ||\omega||_2^2, \qquad (2)$$

with $\Omega = \{\omega \in \mathbb{R}_+^N,\ with\ \sum_{i=1}^{N_{co}} \omega_i = 1\ and\ \omega_i = 1/N_{tr}\ \forall\ i = N_{co}{+}1, ..., N\}$, where $||\omega||_2$ is the Euclidian norm and $\mathbb{R}_+$ denotes the positive real line. N_{co} and N_{tr} are the number of untreated and treated units, respectively. Similarly, T_{pre} is the number of pre-treatment periods. ζ is a regularization parameter to increase dispersion and ensure unique weights, it is defined in Arkhangelsky et al. (2021). Contrary to traditional synthetic control unit weights, these SDID weights do not aim to find comparable regions in absolute terms conditional on covariates, but rather assigns weights to align pre-treatment trends in the (adjusted) outcome.

Time weights are computed to align pre- and post-treatment periods for untreated units:

$$\left(\widehat{\lambda}_0, \widehat{\lambda}^{sdid}\right) = \underset{\lambda_0 \in \mathbb{R}, \lambda \in \Lambda}{\arg\min} \sum_{i=1}^{N_{co}} \left(\lambda_0 + \sum_{t=1}^{T_{pre}} \lambda_t Y_{it} - \frac{1}{T_{post}} \sum_{t=T_{pre}+1}^{T} Y_{it} \right)^2 + \zeta^2 N_{co} ||\lambda||^2, \qquad (3)$$

with $\Lambda = \{\lambda \in \mathbb{R}_+^T,\ with\ \sum_{t=1}^{T_{pre}} \lambda_t = 1\ and\ \lambda_t = 1/T_{post}\ \forall\ t = T_{pre} + 1, ..., T\}$, where the regularization term ensures unique weights and is very small.

In essence, SDID estimates the ATT, $\widehat{\tau}^{sdid}$, from a weighted two-way fixed-effects regression. Compared to SDID, standard difference-in-differences (DID) approaches use an unweighted two-way fixed-effects regression, thus relying on parrallel pre-treatment trends in aggregate data. Synthetic control (SC) relaxes this requirement but uses only unit-specific weights and does not explicitly weigh time periods optimally. Contrary to SC method, SDID additionally allows for level differences between treatment and synthetic control units in estimating optimal weights. Following this rationale, Arkhangelsky et al. (2021) argue that SDID is more flexible compared to DID and SC methods.

4.2 Handling covariates

We then follow the procedure for handling covariates outlined in Arkhangelsky et al. (2021) and refined in Clarke et al. (2023). In contrast to SC approaches that find optimal unit weights by balancing observed covariates across treated and control units, SDID uses a latent factor model and balances unobserved factors to find weights and achieve consistency. Handling covariates in this setting is treated as a pre-modeling approach, in which the outcome variable is adjusted by covariates before estimation. The procedure does not put any stationarity requirements on the covariates, i.e., they can be time-varying. This adjustment procedure contains two steps. In the first step, we estimate the coefficients of the covariates. To obtain estimates that are unconfounded by the treatment itself, we follow Kranz (2022) and exclude the treated unit from estimation. We run the following model:

$$Y_{it}^{co} = \alpha_i + \gamma_t + X_{it}^{co}\beta + u_{it}, \tag{4}$$

where the super-script *co* indicates control units, Y_{it}^{co} measures CO2 emissions from road transport, X_{it}^{co} collects covariates and may include Covid-related effects (i.e. the Covid stringency index and Covid cases), the number of commuters, and the share of employed persons usually working from home, fuel prices, freight transportation, GDP per capita, and population. To capture differences between regions and time, we can include region-specific effects, α_i, and time-specific effects, γ_t. In a second step, we adjust the outcome variable for the aforementioned effects for all units:

$$\widehat{Y}_{it}^{adj} = Y_{it} - X_{it}\hat{\beta}. \tag{5}$$

Finally, the SDID procedure can then be applied to the adjusted outcome variable.

4.3 Placebo inference and event-study analysis

Arkhangelsky et al. (2021) show that the estimated ATT, $\widehat{\tau}^{sdid}$, is asymptotically normal. This means that conventional confidence intervals can be used to conduct asymptotically valid inference if the asymptotic variance, $\widehat{V}_\tau$, can be consistently estimated: $\tau \in \widehat{\tau}^{sdid} \pm z_{\alpha/2}\sqrt{\widehat{V}_\tau}$. Arkhangelsky et al. (2021) propose several estimators for the asymptotic variance (bootstrap, jackknife, placebo). But in cases where there is only one treated unit (i.e., $N_{tr} = 1$), only placebo estimates are well defined. The idea of this procedure is to replace the exposed unit with unexposed units, then randomly assign those units to a placebo treatment and compute a placebo ATT. This is repeated many times to obtain a vector of placebo ATTs. The variance of this vector can then be used to obtain an estimate for the asymptotic variance.

To evaluate the robustness of the results, we perform an event-study analyses, which enable us to study the dynamics of the policy effect and allow us to evaluate the credibility of pre-treatment parallel trends. We follow the discussion in Clarke et al. (2023) on how to compute these estimates manually. In principle, we want to estimate the differences in the outcome variable between treated and the non-treated synthetic control region for each time period t. This allows us to evaluate parallel pre-treatment trends by studying whether these differences changed over time prior to the policy adoption. Additionally, we can study the evolution of the treatment over each post-treatment period.

The difference at each time period t is given by:

$$(\bar{Y}_t^1 - \bar{Y}_t^0) - (\bar{Y}_{base}^1 - \bar{Y}_{base}^0), \tag{6}$$

where 1 indicates a treated unit and 0 the non-treated synthetic control unit. The first term in brackets calculates the difference in mean CO2 emissions at time period t for treated and control unit. The second term in brackets captures the difference between the pre-treatment baseline means of these units. The baseline outcomes are weighted aggregates over pre-treatment periods rather than arbitrarily chosen time periods (as is usually done in DID applications). Confidence bands around these estimates can be generated with a placebo-based approach as follows. 1) exclude treated units (i.e., Luxembourg) from the sample, 2) randomly assign treatment to a region, 3) compute the ATT for this placebo treatment. This procedure can be done many times and we can then draw from the distribution of the results to create confidence bands around the quantity estimated by (6) for each time period t.

5 Results and robustness

This section reports our main results as well as several robustness checks. We study several model specifications, which are outlined in Section 5.1. These include models without any covariates, with COVID-related covariates, and one with a set of additional controls. Section 5.2 tests the robustness of the main results. These checks include specifications that exclude statistically insignificant controls from the main specification as well as results from standard DID procedures. We find that our results are robust against these checks.

5.1 Results

We provide results for three different model specifications. The first one does not adjust emissions for covariates; it is based on Equation (1), where Y_{it} is the log of per capita CO2 emissions from road transport. The second specification adjusts the outcome variable for COVID-related variables as described in Section 4.2. The auxiliary regression is given by:

$$\begin{aligned} log(CO2/cap)_{it}^{co} = & \alpha_i + \gamma_t + \beta_1 asinh(cases)_{it}^{co} + \beta_2 asinh(nvrwfh)_{it}^{co} + \\ & \beta_3 asinh(wfh)_{it}^{co} + u_{it}, \end{aligned} \tag{7}$$

where the outcome variable is log of road-transport CO2 emission per capita. It is regressed on the inverse hyperbolic sine ($asinh$) of Covid cases, of people usually working from home (wfh), and of people working in Luxembourg and never working from home ($nvrwfh$). We use the inverse hyperbolic sine transformation on covariates that include zero-values because the natural logarithm of zero is undefined and the transformation approaches the natural log.[4] The third specification is our main specification and adjusts

[4]The interpretation of the coefficients of the covariates as elasticities in these cases is sensitive to the size of the untransformed average value of the covariates. As suggested by Bellemare and Wichman (2020), we multiply these covariates by a constant to generate average values greater than 10, which provides stable elasticities. The reported coefficients appear to be robust in our specifications.

the outcome variable for additional covariates based on:

$$\begin{aligned} log(CO2/cap)^{co}_{it} =& \alpha_i + \gamma_t + \beta_1 asinh(cases)^{co}_{it} + \beta_2 asinh(nvrwfh)^{co}_{it} + \\ & \beta_3 asinh(wfh)^{co}_{it} + \beta_4 log(gdp)^{co}_{it} + \beta_5 log(ei)^{co}_{it} + \\ & \beta_6 diesel^{co}_{it} + \beta_7 petrol^{co}_{it} + \beta_8 log(frt)^{co}_{it} + u_{it}. \end{aligned} \tag{8}$$

The set of covariates that we consider in this specification additionally includes: log of real gdp per capita and energy intensity, ei, measured as average CO2 emissions of newly registered vehicles. Real diesel and petrol prices, and log of freight transport measured as tonnes of goods loaded in Luxembourg. Estimation results for the auxiliary regressions based on Specifications (8) and (7) are shown in Table B.1 in Appendix B.

We provide results for the ATT for the period that the treatment is in effect, i.e., 2020-2021, as well as an event-study analysis over the period 2016-2021 in Figure 5 for different specifications. Results for the ATTs are shown in Figure 5a and the event-study estimates are shown in Figure 5b. Estimates are based on the following model specifications that differentiate in the way they adjust the outcome variable. 1) not adjusting for covariates - no covariates, 2) adjusting only for Covid-related effects - only COVID covariates, and 3) adjusting for the full set of covariates - all covariates. The control units that contribute to the synthetic control together with their respective weights for the third specification are graphically shown in Figure C.1 in Appendix C. The regions with the largest weights come from Belgium, Hungary, Italy, Netherlands, and Poland. Regions from Denmark, Germany, Finland, and Spain enter the synthetic control with smaller weights.

Table C.1 in Appendix C shows the NUTS 2 regional code and the name of the region together with the specific unit weights assigned to them. Additionally, the table gives realizations of pre-treatment control variables for 2019. These values are quite heterogeneous across controls as well as compared to Luxembourg. This highlights the difference in SDID compared to SC. While the latter tries to match the treated unit to a synthetic control in absolute levels, the former assigns weights to align pre-treatment trends. These trends do not necessitate that the magnitude of controls match well but rather focus on their trajectories before treatment.

Figure C.2 in Appendix C shows the evolution of pre-treatment trends for Luxembourg (black) as well as different averages over different groups of control regions. These include the average pre-treatment trend in the adjusted outcome variable over all regions, the unweighted average over regions that received a positive weight, and the weighted average across control regions according to the assigned SDiD unit weights. Figure C.2a shows the absolute level of trends, while Figure C.2b standardizes the trends so that they are visually more easily comparable.

We can see from these normalized trends that pre-treatment trends for Luxembourg and the average across all regions shows the biggest visual difference in trends. The unweighted average across regions that received a positive weight is a much better fit. The best fit seems to be between Luxembourg and the weighted average according to the SDID unit weights. This visual inspection affirms the notion that SDID assigns unit weights to create a synthetic control that more comparable to Luxembourg pre-treatment compared to a simple average of NUTS2 regions.

Belgium, Denmark, Germany, Finland, and the Netherlands are among the EU countries with the highest GDP per capita and thus most comparable to Luxembourg in this respect. While Poland and Italy have the highest motorization rate after Luxembourg. It is therefore quite reasonable that the regions contributing to the synthetic control are taken from these countries.

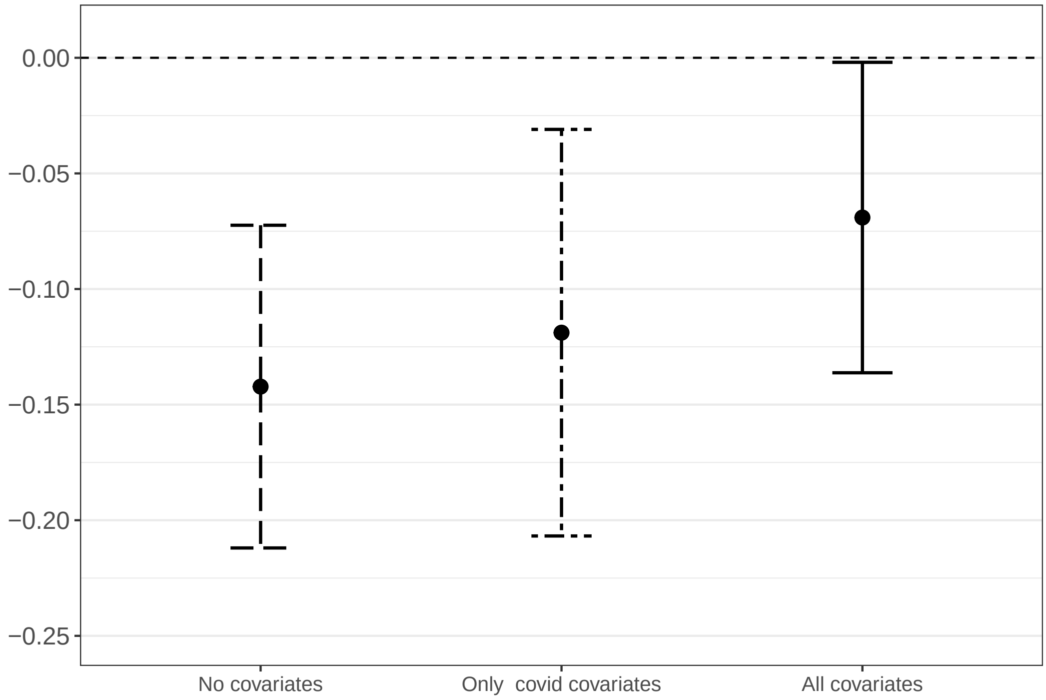
We noted that while Luxembourg experienced a decrease in commuters in the years after the pandemic, the magnitude of these changes was not particularly strong relative to other EU regions. This observation extends to the regions of the synthetic control. Most of these experienced a decrease in the year immediately following the pandemic. Changes in commuting from 2020-2021, however, are more diverse. Some regions experienced a further drop in commuters (as did Luxembourg), while others saw an increase. Only regions in the Netherlands saw a further strong decrease. The other regions show a mixed picture with overall small changes in magnitude.

Overall, the regions constituting the synthetic control show a very similar pattern in commuting changes from 2019-2020. From 2020-2021, most regions experienced only small adjustments in commuting. We believe that this strengthens the credibility of our results because Luxembourg did not experience a strong drop in commuters relative to the synthetic control regions.

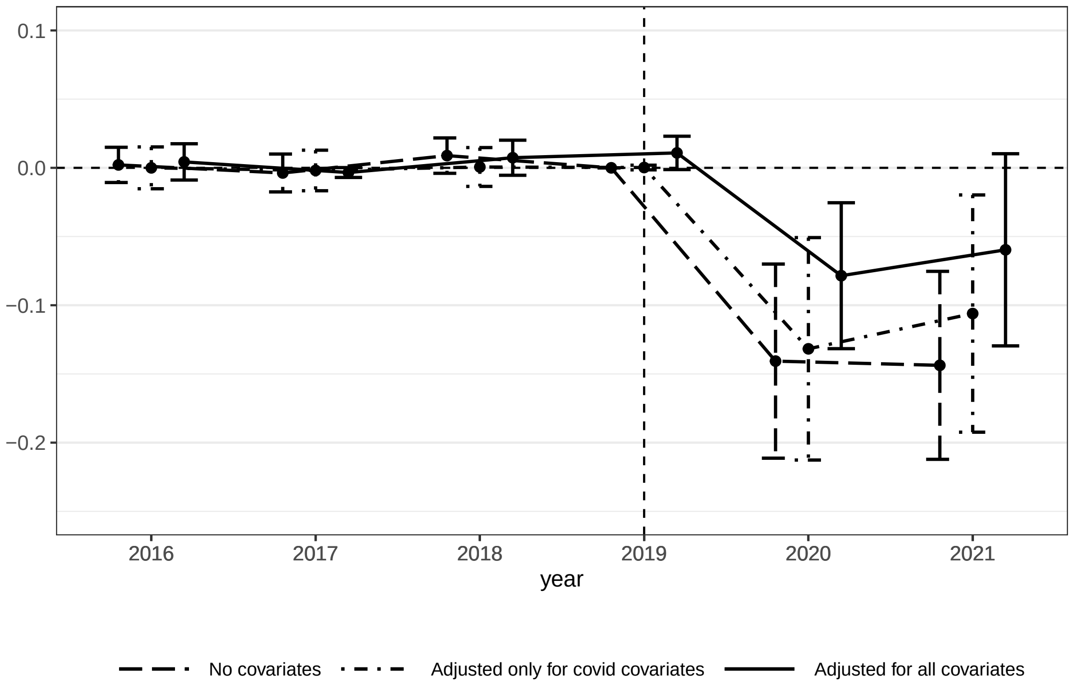
The estimated ATTs for the specification including all covariates indicate an effect at around -0.65, i.e., a 6.9% reduction in transport CO2 emissions as a response to the free-

Figure 5: ATTs and event study estimates of the estimated impact of free public transport on road emissions (CO2) per capita in Luxembourg for different model specifications with 95% confidence bands based on placebo estimates

(a) ATTs since treatment in 2020



(b) Event study estimates for 2016-2021



public transport policy implemented in March 2020. This is less in magnitude compared to controlling only for Covid cases, which yields an estimated ATT of around −11.8%. The specification with no covariates provides the lowest estimated ATT at almost −15%. All estimates are statistically significant at the 5% significance level. The event-study analysis shows no violation of parallel pre-treatment trends for all specifications. Post-treatment effects show statistical significance in 2020 for all three specifications. In 2021, the confidence intervals based on the specifications that adjust the outcome variable slightly cross the dashed zero-line at the 5-% significance level.

5.2 Robustness tests

We have so far studied the three specifications shown in Figure 5, where the main specification is the one including all covariates. We now want to examine the sensitivity of our main results to alternative model specifications. It may be reasonable to assume that people working from home and people commuting to work capture in part similar dynamics (the correlation is around 0.6). We want to test the sensitivity of our results by either dropping one or the other from our specifications. Additionally, from Table B.1, we can see that the coefficient for $log(frt)$ (log of freight transport) is statistically insignificant.

We estimate the following specifications, all of which exclude some combination of these coefficients from the adjustment of the outcome variable. Specifically, we estimate: a model excluding controls for freight transport (Spec 1), a model omitting controls for working from home (Spec 2), and a model that excludes both of these covariates (Spec 3), one that excludes the commuting variable, $nvrwfh$ (Spec 4), and one that excludes both the commuting and freight controls (Spec 5). The results of the sensitivity analyses are displayed in Figure D.1 and Table D.1 in Appendix D. All five alternative specifications show similar estimates to our main specification including all covariates. The estimated ATTs are all just slightly below our main specification, which yields an estimate of around −6.9%.

It is particularly encouraging to observe that the estimates derived from these 5 different model specifications are comparable in magnitude both to our main results and to each other. This consistency underlines the robustness of our findings and confirms their reliability in the inclusion and exclusion of various controls. To further establish the robustness of our results, we compare the three specifications from Figure 5 to standard DID techniques, thus testing the robustness of our results to different model assumptions. The results are displayed in Figure E.1 in Appendix E. The magnitudes of the estimates are slightly larger for all three specifications in comparison to our main results.How the results of the DID analysis are still consistent with our primary results and provide additional validation of our main findings.

6 Discussion

We estimate the ATT of Luxembourg's free public transport policy, introduced in 2020, on road transport CO2 emissions to be approximately -6.9%. We hypothesize that this observed reduction is due to a modal shift from private motorized transport to public transport. In this section, we supplement our causal findings with descriptive data on Luxembourg's traffic volumes to provide further substance to our hypothesis. We analyze traffic count data available on Luxembourg's open data portal (Gouvernement du Grand-Duché de Luxembourg, 2023). The data, compiled by the Administration des Ponts et Chaussées (Luxembourg Bridges and Roads Administration), includes daily traffic counts. These counts are measured by CCTV cameras placed at various points on the roads. We aggregate the number of bi-directional car counts at each traffic post, for each month, over the period 2018 to 2022 by canton. We only include traffic posts that have no missing data for each month and each year during this period. Figure F.1 in Appendix F illustrates where these traffic posts are located in Luxembourg. Additionally figure F.1 also maps Luxembourg's regional bus network (RGTR network) (grey), tram line (red), and the National Rail network (CFL) (pink). The geospatial data of the public transport networks are also obtained from Luxembourg's open data portal (Gouvernement du Grand-Duché de Luxembourg, 2024).[5] The traffic posts circled have all experienced a decrease in annual bi-directional car traffic volume compared to 2019. These traffic posts are largely situated close to Luxembourg city and public transport networks. The traffic posts with bolded circles represent the 10 posts with the largest decrease in bi-directional car traffic volume compared to 2019. Figure F.2 in Appendix F shows the annual bi-directional traffic volume for the years 2018 to 2021, for these top ten traffic posts. Examining the

[5] The latest shapefiles available are for 2018

total annual traffic volume, we observe a slight upward trend in traffic counts up to the year 2019. As expected, there is a decline in 2020 across these posts, coinciding with the COVID-19 pandemic. However, the traffic counts for the years 2019 are lower than the pre-pandemic levels of 2019.

We now want to discuss whether our estimated effect size is reasonable. Consider the following back-of-the-envelop calculations. We estimate a reduction in CO2 emissions from road transport of 6.9%. Following Bigi et al. (2023), let us assume a modal split for private vehicles and public transport of around 80 and 15 percent, respectively. Further, assume that the emission reduction is due to a modal change from private vehicles to public transport. This then gives an estimated increase of public transport usage of around 36%.

To assess credibility of this effect, we utilize public transport usage data for Luxembourg. Specifically, we turn to data on the average daily number of people using trams on weekdays from OECD (2023). In February 2020, this average tram usage was at around 31,000 persons. This increased to around 36,000 in February 2021 and to around 53,000 in February 2022. This amounts to an increase of around 15% and 32% from 2020-2021 and 2021-2022, respectively. These numbers are well in line with our estimates, suggesting that they are reasonable. Additionally, we can relate these results to the LUXmobile survey, carried out by the Luxembourg City Council (Luxmobile, 2020). This survey suggests that the free public transport policy has led to an increase in public transport usage of around 30% in 2022, further adding credibility to our estimate.

7 Conclusion

We estimate the ATT of the free public transport policy introduced in Luxembourg in 2020 to be around -0.069, controlling for all covariates. This implies a reduction in CO2 emissions from road transport of around 6.9%. The results show considerable stability across a range of model specifications that take into account factors related to the COVID-19 pandemic, fuel prices, the prevalence of remote working, and commuting patterns. Furthermore, our results are consistent with the descriptive evidence from traffic volume data and the evidence from the LUXmobile survey, which indicates an increase in public transport use as a result of the free public transport policy (Luxmobile, 2020).

The consistency of our results leads us to conclude that this is a statistically significant causal effect, indicating a behavioral shift from private car use to public transport.

Our findings have a high policy relevance. The reduction in CO2 emissions from road transport resulting from Luxembourg's free public transport policy provides compelling evidence of the effectiveness of such policies in contributing to climate change mitigation efforts. This insight is particularly relevant for policymakers in urbanized, affluent areas with well-developed public transport systems, similar to Luxembourg. As countries strive to meet increasingly ambitious climate targets, the integration of free public transport policies with other sustainable transport and urban planning initiatives could offer a holistic solution to reducing CO2 emissions and fostering a sustainable future.

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Appendix A

Table A.1: Data description

Variable *(variable name)*	Description	Measurement	Sources
CO2 emissions $log(co2)$	CO2 emission from road transport sector. IPCC-1996 sector category 1.A.3.b	*log* of CO2 per capita	EDGARv8
GDP $log(gdp)$	Regional GDP by NUTS 2 regions	*log* of million purchasing power standard per inhabitant	Eurostat regional statistics
covid cases $asinh(cases)$	Daily number of new covid 19 cases aggregated to the annual level, for each NUTS2 region	inverse hyperbolic sine of number of cases	European region tracker
commuters $asinh(nvrwfh)$	Number of persons who never worked from home in the reference period of four weeks preceding the end of the reference week for all NUTS 2 region, which are the location of the workplace irrespective of the location of residence	inverse hyperbolic sine of number of commuters	EU Labour Force Survey
work from home $asinh(wfh)$	The number of persons who usually worked from home in the reference period of four weeks preceding the end of the reference week. For NUTS 2 regions which are the location of the workplace with the location of residence in the same country	inverse hyperbolic sine of the number of workers	EU Labour Force Survey
emissions intensity $log(ei)$	Avg CO2 emissions for new passenger cars	*log* of CO2/km	Eurostat
diesel price *diesel*	Avg annual price of diesel adjusted for inflation	Euros per liter	Eurostat weekly oil bulletin
petrol price *petrol*	Avg annual price of petrol adjusted for inflation	Euros per liter	Eurostat weekly oil bulletin
freight $log(frt)$	Total good loaded in the NUTS 2 region	*log* of million tonne per km	Eurostat regional statistic

Appendix B

Table B.1: TWFE regression for specification projected with all covariates and only adjusted for COVID-related controls

	(1)	(2)
asinh(cases)	-0.0265***	-0.0112
	(0.00540)	(0.00765)
asinh(nvrwfh)	0.0884***	0.147**
	(0.0309)	(0.0609)
asinh(wfh)	-0.0189**	-0.0593***
	(0.00724)	(0.0112)
log(gdp)	0.526***	
	(0.0831)	
log(ei)	0.287***	
	(0.0492)	
diesel	-0.791***	
	(0.0967)	
petrol	0.433***	
	(0.130)	
log(frt)	0.00701	
	(0.0122)	
Obs	792	792
N	132	132
T	6	6

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Dependent variable is log of CO2 per captia, $log(co2)$, standard errors are in parantheses and clustered at the regional level. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.10$

Appendix C

Figure C.1: Unit weights - all covariates

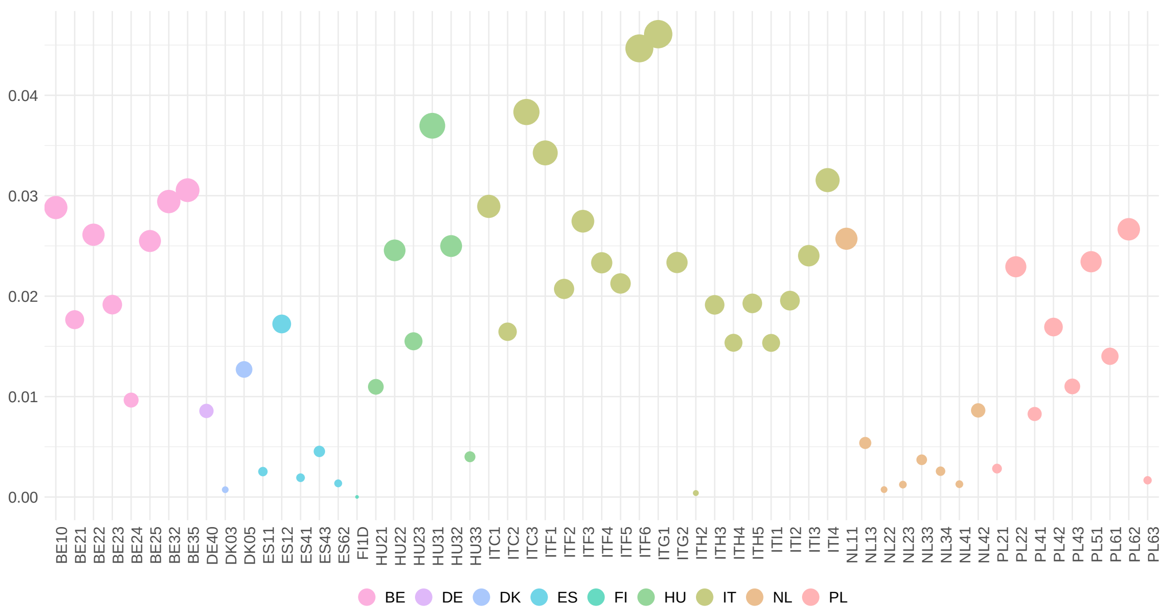


Table C.1: Summary values of selected variables in 2019 of NUTS 2 regions that received positive weights

NUTS2	Name	Weights	CO2pc	GDPpc	EI	NvrWFH	WFH	Diesel	Petrol
LU00	**Luxembourg**	-	8.287867	78700	133	348.675	33.899	1.0387	1.1432
ITG1	Sicilia	.0460852	1.324144	18400	119.4	1284.265	31.611	1.4324	1.5237
ITF6	Calabria	.0446712	1.568642	17700	119.4	512.706	14.867	1.4324	1.5237
ITC3	Liguria	.038334	1.164884	32900	119.4	582.16	28.682	1.4324	1.5237
HU31	Észak-Magyarország	.0369661	1.662413	15100	129.7	426.951	4.25	1.1198	1.0703
ITF1	Abruzzo	.0342636	2.498864	25700	119.4	466.533	19.18	1.4324	1.5237
ITI4	Lazio	.0315534	1.0559	35200	119.4	2285.137	102.913	1.4324	1.5237
BE35	Prov. Namur	.0305506	3.872224	24500	121.5	125.367	14.525	1.3334	1.2908
BE32	Prov. Hainaut	.0294199	2.387068	22800	121.5	322.539	37.43	1.3334	1.2908
ITC1	Piemonte	.0289401	1.957292	32000	119.4	1707.208	75.301	1.4324	1.5237
BE10	Rég. de Bruxelles-Capitale	.0288217	.4279352	63400	121.5	483.185	31.066	1.3334	1.2908
ITF3	Campania	.0274606	.7965805	19500	119.4	1519.748	42.197	1.4324	1.5237
PL62	Warmińsko-mazurskie	.0266593	2.164641	15600	130.4	477.188	33.594	1.1201	1.1095
BE22	Prov. Limburg (BE)	.0261186	2.470908	29700	121.5	248.926	21.71	1.3334	1.2908
NL11	Groningen	.0257157	1.429476	36000	98.4	185.302	38.054	1.2825	1.5581
BE25	Prov. West-Vlaanderen	.0254914	2.015859	35700	121.5	375.179	50.194	1.3334	1.2908
HU32	Észak-Alföld	.0249882	1.409951	14700	129.7	593.312	4.625	1.1198	1.0703
HU22	Nyugat-Dunántúl	.0245595	1.920265	22200	129.7	438.736	4.246	1.1198	1.0703
ITI3	Marche	.0240278	1.749979	28400	119.4	597.778	19.142	1.4324	1.5237
PL51	Dolnośląskie	.0234284	1.559153	24900	130.4	1015.523	63.135	1.1201	1.1095

Continued on next page

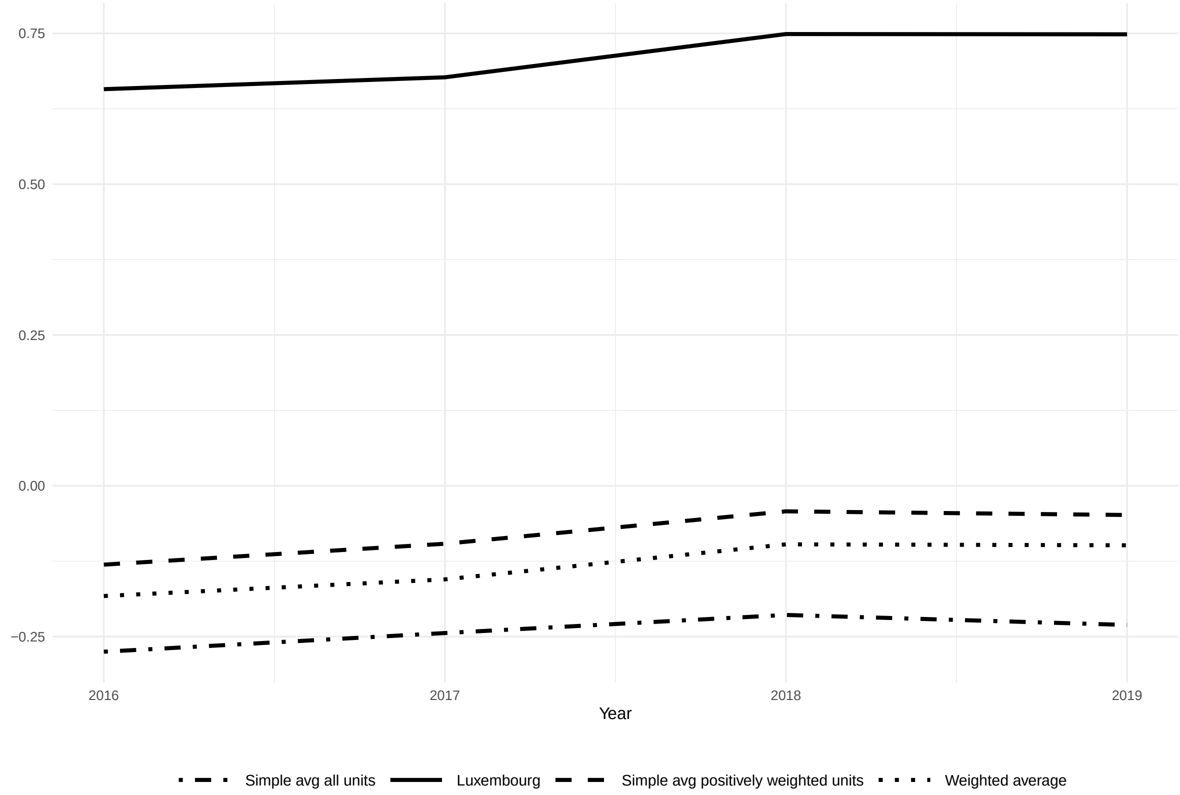
Table C.1 continued from previous page

NUTS2	Name	Weights	CO2pc	GDPpc	EI	Commute	WFH	Diesel	Petrol
ITG2	Sardegna	.0233507	2.561578	22000	119.4	561.487	16.294	1.4324	1.5237
ITF4	Puglia	.0233227	1.051745	19600	119.4	1167.695	25.646	1.4324	1.5237
PL22	Śląskie	.0229276	1.084913	23400	130.4	1622.908	91.718	1.1201	1.1095
ITF5	Basilicata	.0212645	2.996321	23300	119.4	188.589	4.191	1.4324	1.5237
ITF2	Molise	.0207205	3.354921	21900	119.4	101.967	2.375	1.4324	1.5237
ITI2	Umbria	.0195545	1.920073	26600	119.4	336.737	12.897	1.4324	1.5237
ITH5	Emilia-Romagna	.0192799	1.906196	36600	119.4	1950.986	84.006	1.4324	1.5237
BE23	Prov. Oost-Vlaanderen	.0191552	1.888781	33500	121.5	478.839	48.609	1.3334	1.2908
ITH3	Veneto	.0191355	1.750784	34200	119.4	2043.725	88.04	1.4324	1.5237
BE21	Prov. Antwerpen	.0176584	1.479478	43400	121.5	573.013	54.575	1.3334	1.2908
ES12	Principado de Asturias	.0172325	2.084811	25000	121.3	337.108	25.691	1.1645	1.2443
PL42	Zachodniopomorskie	.0169248	1.733621	19000	130.4	600.91	31.089	1.1201	1.1095
ITC2	Valle d'Aosta/Vallée d'Aoste	.0164573	4.806325	39000	119.4	57.961	1.897	1.4324	1.5237
HU23	Dél-Dunántúl	.0155055	2.265898	15500	129.7	338.673	3.979	1.1198	1.0703
ITH4	Friuli-Venezia Giulia	.0153587	2.473126	32700	119.4	481.826	24.463	1.4324	1.5237
ITI1	Toscana	.0153478	1.677962	33100	119.4	1521.733	67.87	1.4324	1.5237
PL61	Kujawsko-pomorskie	.0140143	1.761975	18200	130.4	713.429	33.875	1.1201	1.1095
DK05	Nordjylland	.0127028	2.361858	32900	111.9	199.535	21.74	1.3608	1.5686
PL43	Lubuskie	.0110128	2.407628	18500	130.4	372.141	9.518	1.1201	1.1095
HU21	Közép-Dunántúl	.0109734	1.923086	21100	129.7	453.529	3.476	1.1198	1.0703
BE24	Prov. Vlaams-Brabant	.0096522	2.068579	39900	121.5	323.363	30.611	1.3334	1.2908
NL42	Limburg (NL)	.008625	1.881989	35000	98.4	384.305	68.802	1.2825	1.5581
DE40	Brandenburg	.0085718	3.522108	27400	131.2	373.286	57.475	1.1892	1.3425
PL41	Wielkopolskie	.0082682	1.616404	24800	130.4	1347.876	87.625	1.1201	1.1095
NL13	Drenthe	.0053832	3.091486	27000	98.4	163.221	32.616	1.2825	1.5581
ES43	Extremadura	.0045429	3.320498	20700	121.3	353.452	19.641	1.1645	1.2443
HU33	Dél-Alföld	.0040102	1.601193	16500	129.7	534.09	3.244	1.1198	1.0703
NL33	Zuid-Holland	.0037091	1.151502	38400	98.4	1111.512	247.642	1.2825	1.5581
PL21	Małopolskie	.0028314	1.235496	20800	130.4	1165.436	66.144	1.1201	1.1095
NL34	Zeeland	.0025722	1.630755	31500	98.4	123.797	30.612	1.2825	1.5581
ES11	Galicia	.0025317	2.153037	25600	121.3	975.87	59.897	1.1645	1.2443
ES41	Castilla y León	.0019238	4.726597	26800	121.3	888.02	47.452	1.1645	1.2443
PL63	Pomorskie	.0016685	1.347721	22200	130.4	811.075	75.224	1.1201	1.1095
ES62	Región de Murcia	.001362	1.794109	23300	121.3	549.355	25.372	1.1645	1.2443
NL41	Noord-Brabant	.0012802	1.829372	40200	98.4	869.949	184.977	1.2825	1.5581
NL23	Flevoland	.0012364	2.423461	29300	98.4	113.304	24.363	1.2825	1.5581
NL22	Gelderland	.0007398	2.004177	33500	98.4	656.286	173.673	1.2825	1.5581
DK03	Syddanmark	.0007304	2.122641	35300	111.9	412.184	46.22	1.3608	1.5686
ITH2	Prov. Autonoma di Trento	.0003959	2.652894	39600	119.4	225.226	8.632	1.4324	1.5237
FI1D	Pohjois- ja Itä-Suomi	.0000101	3.307658	28300	115.3	411.308	58.802	1.3593	1.4714

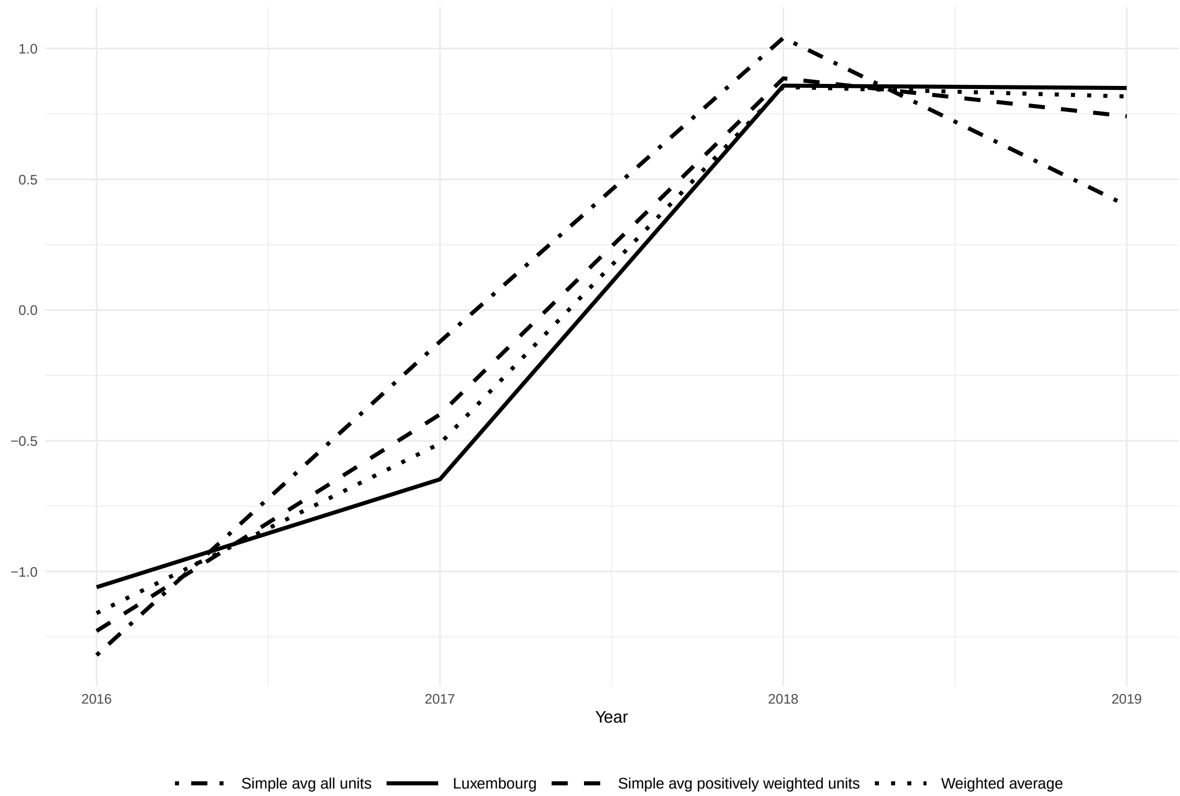
Note: *Weights* refer to unit weights assigned by the SDID method. *CO2 pc* is CO2 emissions measured in tonnes per capita. *GDP pc* is GDP per capita in Purchasing Power Standards. *EI* is the average CO2 emissions per km from new passenger cars. *Commute* refers to all persons commuting to the NUT2 region. *WFH* is the proportion of people working from home. *Diesel* is the annual average real price of diesel. *Petrol* is the annual average real price of petrol. All values (except weights) are for 2019.

Figure C.2: Pre-treatment trends of the adjusted log CO2 per capita emissions

(a) Absolute level



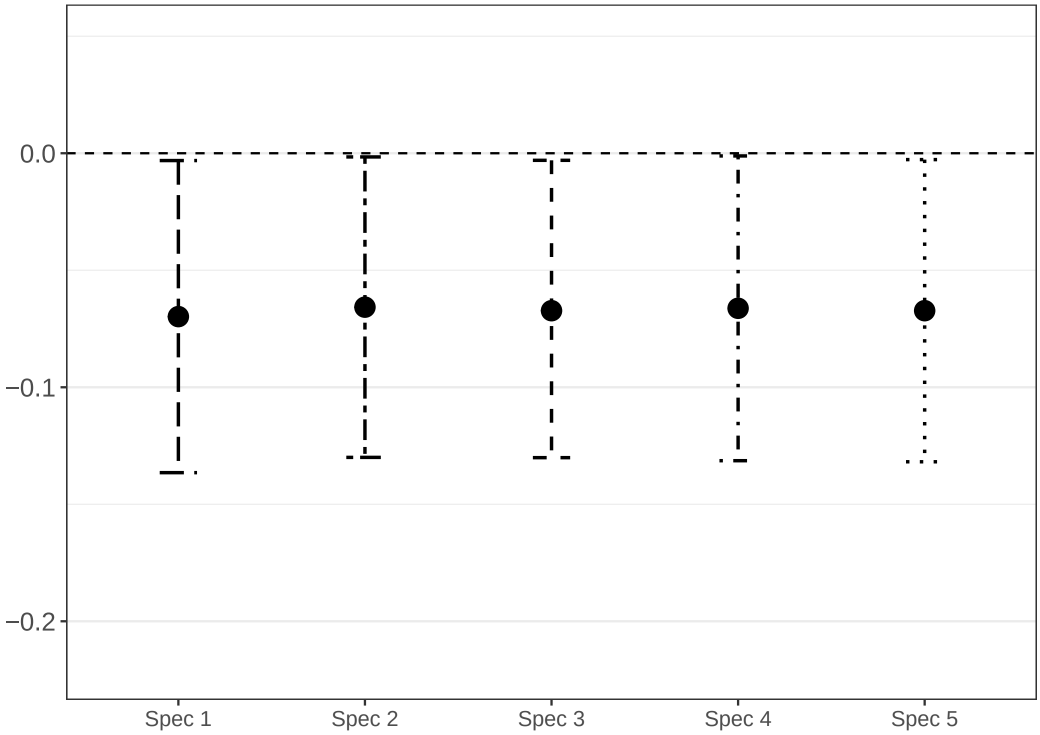
(b) Normalized outcome



Notes: Luxembourg is the pre-treatment time series trend for Luxembourg treated unit. *Simple avg all units* is the pre-treatment average trend of all units in the donor pool. *Simple avg positively weighted units* is the pre- treatment average trend of the units in the donor pool that received positive weights. *Weighted average* is the pre-treatment weighted average of the units that received a positive weights.

Appendix D

Figure D.1: ATTs across different model specifications



Notes: Spec 1 excludes controls for freight transport; Spec 2 excludes controls for working from home; Spec 3 excludes controls for both freight and working from home, Spec 4 excludes controls for commuting (never working from home); Spec 5 excludes controls for both freight and commuting.

Table D.1: Sensitivity analysis across different model specifications

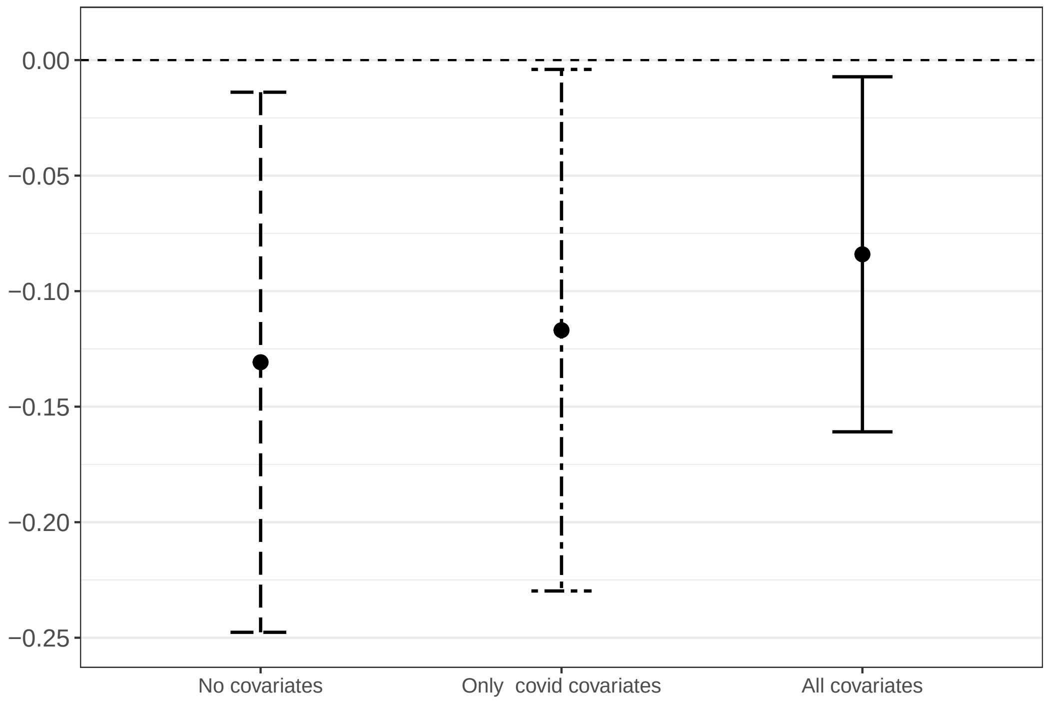
	(1)	(2)	(3)	(4)	(5)
asinh(cases)	-0.0264***	-0.0245***	-0.0243***	-0.0289***	-0.0287***
	(0.00544)	(0.00519)	(0.00521)	(0.00579)	(0.00582)
asinh(nvrwfh)	0.0887***	0.118***	0.119***		
	(0.0310)	(0.0349)	(0.0351)		
asinh(wfh)	-0.0191***			-0.0267***	-0.0269***
	(0.00722)			(0.00615)	(0.00612)
log(gdp)	0.526***	0.562***	0.562***	0.511***	0.511***
	(0.0830)	(0.0866)	(0.0864)	(0.0861)	(0.0860)
log(ei)	0.288***	0.289***	0.290***	0.301***	0.303***
	(0.0490)	(0.0488)	(0.0486)	(0.0501)	(0.0499)
diesel	-0.796***	-0.820***	-0.826***	-0.817***	-0.822***
	(0.0932)	(0.0985)	(0.0949)	(0.0938)	(0.0908)
petrol	0.437***	0.434***	0.440***	0.446***	0.451***
	(0.127)	(0.131)	(0.128)	(0.127)	(0.124)
log(frt)		0.00873		0.00814	
		(0.0122)		(0.0118)	
Obs	792	792	792	792	792
N	132	132	132	132	132
T	6	6	6	6	6

Standard errors in parentheses. Dependent variable is log(co2cap).

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix E

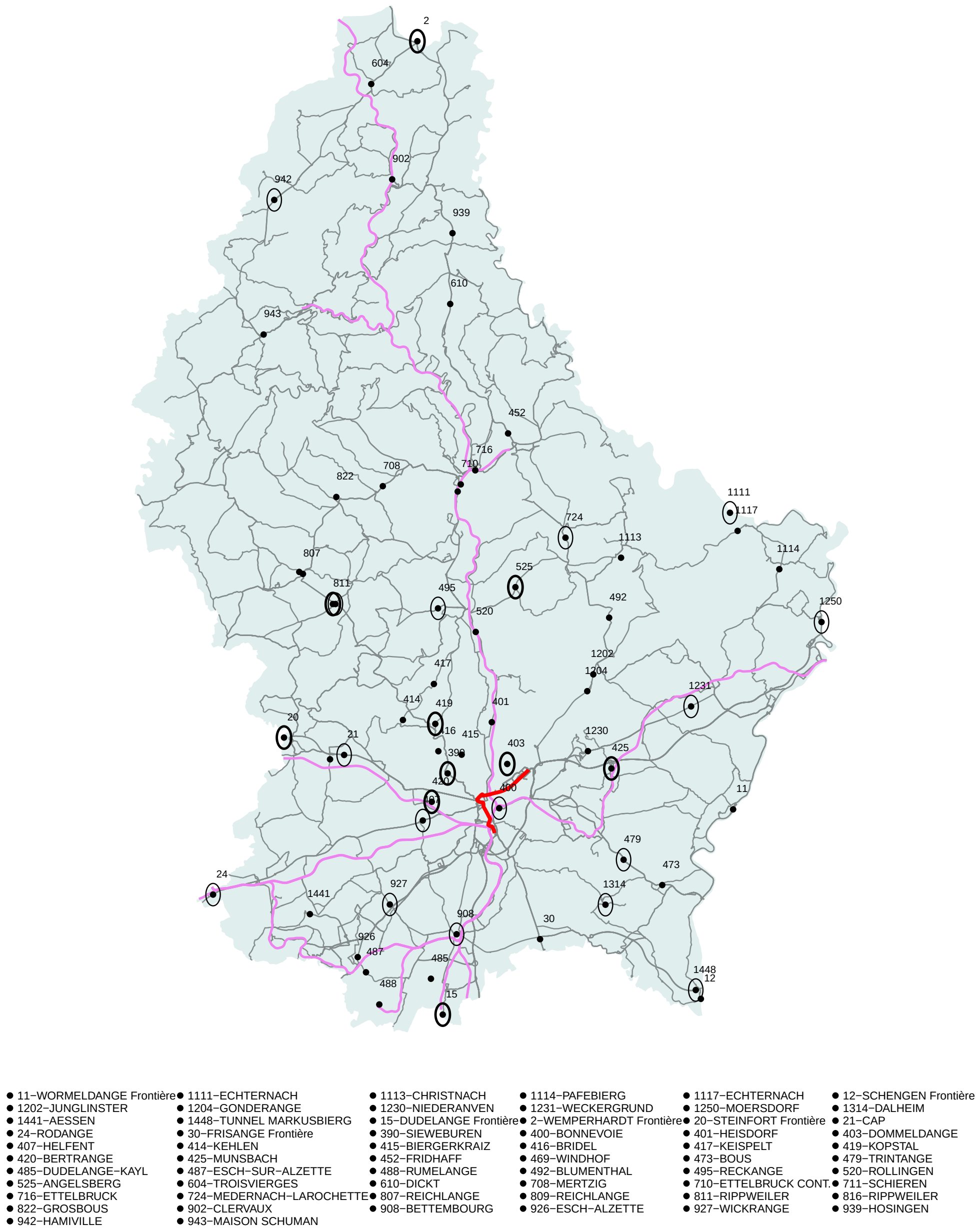
Figure E.1: ATTs using DID approach



Notes: The estimates are based on the following model specifications, which differ in the way they adjust for the outcome variables: 1) not adjusting for covariates - no covariates, 2) adjusting only for Covid-related effects - only COVID covariates, and 3) adjusting for the full set of covariates - all covariates. These three specifications correspond to the three specifications used in the SDID analysis.

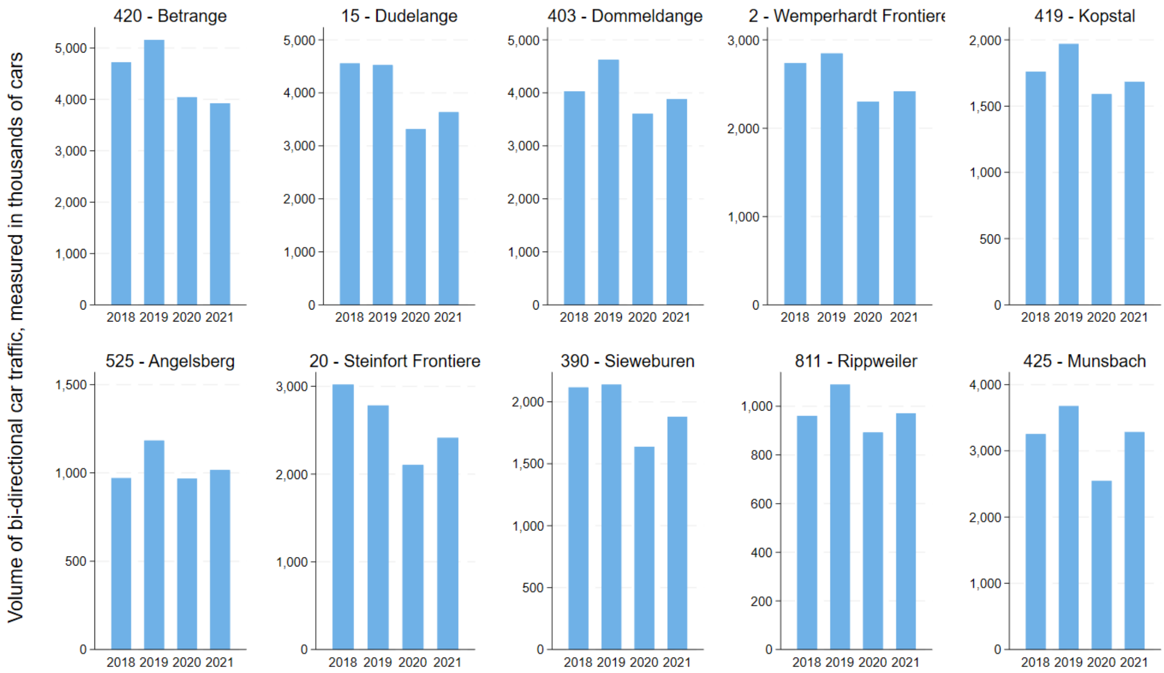
Appendix F

Figure F.1: Luxembourg public transport network and traffic camera posts



Notes: The black dots indicate the location of the traffic posts. The circled dots indicate traffic posts that recorded a decrease in bi-directional car traffic volumes in 2021 relative to 2019. The light grey lines are the regional (RGTR) bus networks. The pink lines are the National rail network. The red line is the tram line. The public transport networks mapped are the networks as of 2018 (the latest available data).

Figure F.2: Volume of bi-directional car traffic



Notes: The figure illustrates the bi-directional car traffic volume of the 10 posts that recorded the largest decrease in car traffic in 2021 relative to 2019. Refer F.1 above for the corresponding location of the traffic posts