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 to make public transport free. We use this unique setting to evaluate the policy's impact on carbon emissions. Synthetic difference-in-differences allows us to identify a suitable control group. We use spatial emission data to construct a panel of NUTS 2 control regions in the EU from 2016 to 2021. Our estimates indicate an average reduction of 6.1% in road transport emissions. We account for potential confounders, such as the COVID-19 pandemic, shifts in commuting behaviors and advancements in vehicle technologies. Robustness checks support the credibility of our results.

Keywords: Emissions, Public Transport, Synthetic DID

JEL Codes: C31, Q54, R48

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1 Introduction

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 transit can encourage a shift from private motorized transport to more environmentally friendly modes. However, despite these benefits, fully free public transport policies are scarce. In March 2020, Luxembourg became the first country in the world to abolish fares on all modes of public transit, including buses, trains, and trams, throughout the country to mitigate transport-related externalities (Research Luxembourg, 2021). Our paper exploits this quasi-experimental setting to empirically quantify its impact on CO2 emissions in Luxembourg's road transport sector. To evaluate the effect of this policy, we use the recently introduced synthetic difference-in-differences method to construct a meaningful counterfactual for Luxembourg and compare the post-intervention outcomes against it (Arkhangelsky et al., 2021).

In our specific setting, we encounter two main identification challenges. First, Luxembourg stands out from other European Union (EU) countries in many ways. It has the highest Gross Domestic Product (GDP) per capita, the highest motorization rate, and the highest per capita CO2 emissions from transport. These unique characteristics make it challenging to find comparable regions to construct a counterfactual scenario for Luxembourg. To address this, we conduct our analysis at the Nomenclature for Territorial Units for Statistics (NUTS) 2 level, as Luxembourg itself constitutes a NUTS 2 region.[1] This level of analysis provides a more appropriate basis for comparison in terms of emission trajectories than entire countries.

The uniqueness of Luxembourg's case also makes it less plausible that the parallel trends assumption required for a difference-in-differences (DID) estimation will hold. Synthetic control (SC) approaches may find a better counterfactual by attaching weights to units that are more similar to Luxembourg than others. However, SC methods require a donor pool of units similar in predictors of the outcome to the treated unit, and weights are assigned to donor units such that the synthetic counterfactual exactly emulates the trajectory of the treated unit's outcome in the pre-period. Given the uniqueness of Luxembourg among EU regions, this requirement is unlikely to be met in our setting. We therefore use the recently proposed synthetic difference-in-differences (SDID) method and construct a counterfactual CO2 emission trajectory for Luxembourg from a pool of donor regions without relying on matches in absolute levels at any stage of the procedure.

The second challenge to identification is linked to variations in mobility patterns that are caused by factors other than the free public transportation policy. The COVID-19

[1]NUTS is an EU classification system that divides countries into three levels. These classifications are used for collecting, developing, and harmonizing European regional statistics, conducting socio-economic analyses, and framing EU regional policies.

pandemic, which coincided with the implementation of the free transport policy, is likely causing such variations. This complicates identification if mobility behavior changed very differently in Luxembourg compared to the control regions. Luxembourg experiences a large inflow of commuters relative to their workforce. Cross-border commuters work in Luxembourg but reside in France, Belgium, or Germany. To study changes in this behavior, we draw on data on working from home and commuting inflow for Luxembourg. Our analysis indicates that Luxembourg's mobility patterns in response to the pandemic were largely consistent with those observed in other EU regions. Additionally, we account for these patterns in our models to enhance the accuracy of our identification strategy. Additionally, countries and regions might have reacted differently to the pandemic, resulting in large variations in the spread of the virus, which might impact mobility behavior in our sample period. To control for such variations, we study and control for daily regional COVID-19 cases in our estimations.

Our potential donor pool for constructing Luxembourg's counterfactual comprises all other European regions at the NUTS 2 level over the period 2016-2021. From this pool, we exclude regions that have implemented any form of public transportation subsidy during the study period (this is elaborated in Section 4). After ensuring a balanced sample, our final donor pool includes 136 NUTS 2 regions and 816 region-time observations. Using this dataset, we estimate that the free public transport policy in Luxembourg led to an average treatment effect on the treated (ATT) of around 6.1%, i.e., to a reduction in CO2 emissions from the road transport sector by 6.1%. Our results are significant at the 95% confidence level. We conduct an event study analysis to verify that parallel trends hold in the pre-treatment period. We conduct various robustness and sensitivity tests, including a placebo test by backdating the policy to 2019, a specification that accounts for fuel tourism effects, and analyzing a more restricted sample of NUTS 2 regions. We also examine the sensitivity of our results to different model specifications and test the robustness of our estimates against fuel-tourism effects. Our findings remained consistent across all these tests.

We contribute to the literature by providing the first causal assessment of a free public transport policy on CO2 emissions. Methodologically, we employ novel approaches to address the unique challenges presented by Luxembourg's distinct characteristics and the concurrent COVID-19 pandemic. Additionally, this study offers a framework for addressing COVID-19 as a potential confounder in similar research contexts. To the best of our knowledge, there is only one other study that directly looks at Luxembourg's free public transportation policy. Bigi et al. (2023) use an agent-based modeling approach and indicate that the policy significantly contributed to a modal shift from private vehicles to public transport. Our findings contribute to this narrative by providing a causal ex-post evaluation of the policy's impact on CO2 emissions.

The existing literature on the effects of *free* public transport on CO2 emissions is still scarce. Tallinn (Estonia) introduced free public transit in 2013 and extended it since. Descriptive work by Cats et al. (2017) found that this policy is associated with 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), which were primarily used during off-peak hours. This suggests that the vouchers were more often utilized for leisure activities rather than reducing car usage. Tomeš et al. (2022) study two massive long-distance fare discount schemes for children, students, and pensioners in Slovakia and the Czech Republic. 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 evaluate the impact on CO2 emissions.

Our paper links to a larger 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 types. The first one 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 type 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 related to the third type 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 (Koch et al., 2022; Kuss & Nicholas, 2022; Winkler et al., 2023).

Literature on public transport provision and improvements is particularly relevant to our study. However, this body of research primarily emphasizes the effects on air quality, with limited attention to other climate impacts. Li et al. (2019), for example, assess the effect of subway expansion on air quality in China, while Lalive et al. (2018) investigate the impact of increased regional rail services in Germany. Additionally, Chen and Whalley (2012) explore the consequences of introducing a new rail transit system in Taipei. 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. Despite observing no average effect, they identify a decrease in air pollution, specifically in cities that initially had higher levels of pollution.

Studies on the effects of fare reductions include, for instance, Aydin and Kürschner Rauck (2023) and Gohl and Schrauth (2024), who examine the impact of the 9-Euro ticket introduced in Germany in 2022 on air quality. Both studies observe 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 find no significant evidence of air quality improvements.

The rest of the paper is organized as follows. Section 2 briefly introduces Luxembourg's free public transport policy. The Data used is detailed in Section 3. The identification strategy is discussed in Section 4. The empirical strategy, including the SDID procedure, is detailed in Section 5. Section 6 provides our empirical results and robustness tests. The results and potential mechanisms are discussed in Section 7. Finally, Section 8 provides concluding remarks.

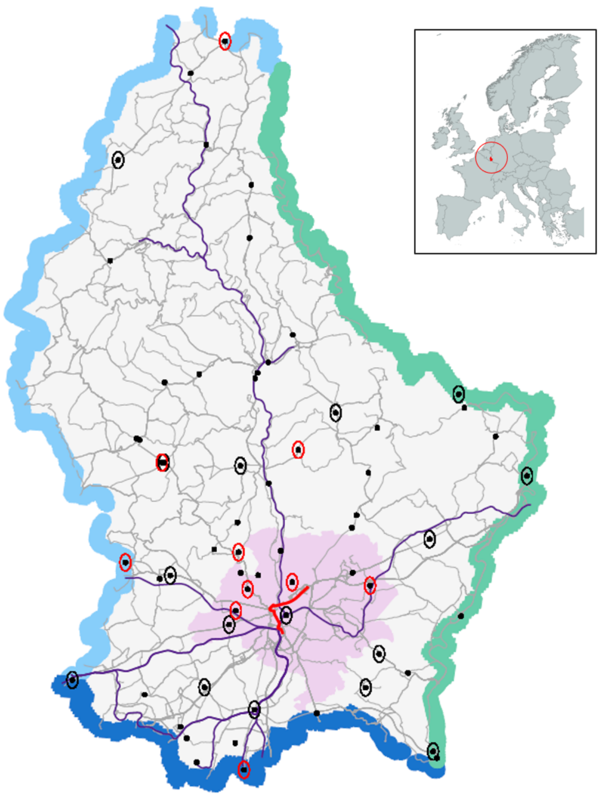
2 Background: Luxembourg and the policy

Luxembourg is a small country in Western Europe and spans an area of about 2,586 km^2, making it one of the smallest countries in the EU. In the NUTS statistical classification, Luxembourg is treated as a single region at all levels. The country hosts several EU institutions, with its economy primarily driven by banking and finance. Despite its small size and population, Luxembourg has the highest GDP per capita among EU countries, at approximately 140,000 USD. The economic hub is concentrated in Luxembourg City, the capital, located in the south. The country experiences a significant daily inflow of commuters from neighboring Belgium, Germany, and France, with around 200,000 people commuting daily, representing a substantial portion of its population of approximately 660,000. Luxembourg has the highest per capita CO2 emissions from transport among EU member states, at around 8,200 kg. It also has the highest car density in the EU, with about 700 cars per 1,000 inhabitants. These characteristics set the country quite far apart from other EU countries.

On March 1, 2020, Luxembourg became the first country in the world to offer free public transport nationwide, available to all residents and visitors regardless of age and income group. Tickets are only required for 1st class travel. This initiative was part of the broader mobility strategy, "Modu.2.0" that aimed at improving the sustainability of the mobility system (Ministère du Développement Durable et des Infrastructures, 2018). Luxembourg designed this policy with the aim of reducing car usage to counter its high car density and significant congestion problems. Before the implementation of this policy, annual revenue for ticket sales in Luxembourg amounted to about 41 million euros, which accounted for approximately 8% of the annual cost of transport system maintenance (Ministère du Développement Durable et des Infrastructures, 2018).

The existing public transportation infrastructure forms the backbone of the policy initiative and comprises buses, trams, and trains. The public transit network is sketched in Figure 1, where bus lines are shown in grey, train lines in pink, and the tram line in red. Buses are the predominant mode of public transportation in Luxembourg and offer quite a comprehensive coverage across the entire country. They 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). Trains additionally cover the country in a star-like network, originating in Luxembourg City and connecting it to cross-border connections (Département de la mobilité et des transports, 2020).

Figure 1: Luxembourg public transport network and traffic camera posts



Note: On the upper righthand side of the figure is a map of Europe with Luxembourg highlighted in red. At the center of the figure is a map of Luxembourg. The light blue side shows the border shared with Belgium, the green side shows the border shared with Germany and the dark blue side shows the border shared with France. 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 dots circled in red show the top 10 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 dark purple lines are the National rail networks. The red line is the tram line. The light pink shaded area is Luxembourg City. The public transport networks mapped are the networks as of 2018 (the latest available data). The traffic posts data and the geospatital data for the public transport data are obtained from Luxembourg's open data portal (Gouvernement du Grand-Duché de Luxembourg, 2023, 2024).

The city of Luxembourg is additionally served by the only tram line in the country, which covers around 10km through 17 stations (Département de la mobilité et des transports, 2024). Before the implementation of the free public transportation policy, Luxembourg charged differentiated public transport fares based on the duration and length of travel. Special rates for children and the elderly were available, as outlined in the Ministerial Regulation of July 14, 2017 - *Règlement ministériel du 14 juillet 2017 fixant les tarifs des transports publics* (Le Ministre du Développement durable et des Infrastructures, 2017). Short-term tickets, valid for a maximum of 2 hours from validation were priced at 2 euros. Long-term tickets, valid for 1, 2, and 3 days, ranged from 4 to 12 euros, while annual network subscriptions were priced at 440 euros.[2]

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 and extensions in the tram line coverage. In 2017, Luxembourg introduced a tram line traversing Luxembourg City, initially connecting 8 stations. The following year saw the line's expansion by 3 more stops. December 2020 marked another 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. Because the extension in 2020 aligns exactly with the free transit policy, we cannot disentangle the two effects and have to study their impact jointly. The most recent extension lies outside our sample period and we do not find evidence that suggests significant effects of the 2017 expansion. We will return to the latter aspect in Section 6.1.

Currently, the tram stretches over 10 kilometers, serves 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). Luxembourg also prioratized improving parking availability, particularly near border areas because of its substantial number of cross-border commuters. Additionally, through negotiations with neighboring transport networks, fares for cross-border transport have been lowered (Ministry of Mobility and Public Works, 2020). Consequently, the new scheme is designed to benefit not only residents but also commuters from neighboring countries. The strategic objective for 2025 is to reduce congestion during peak hours while transporting 20% more people than in 2017.

Figure 1 also illustrates traffic posts in Luxembourg measuring bi-directional car travel volume. The traffic volume data is compiled by the Administration des Ponts et Chaussées (Luxembourg Bridges and Roads Administration) and includes daily traffic counts. We map the points for which we obtain an uninterrupted time series over the period 2018-2021. The traffic posts circled all experienced a decrease in annual bi-directional car

[2]A detailed schedule of public transport fares is available at (Le Ministre du Développement durable et des Infrastructures, 2017).

traffic volume compared to 2019, and the ten red circles experienced the largest drop. The circled traffic posts are largely situated in the vicinity of Luxembourg City and mostly close to public transport networks. Overall, traffic volume increased annually up to 2019 and basically stagnated after 2019, on average. We relate changes in traffic volume to our results more thoroughly in Section 7.

3 Data

We combine the following data to estimate the causal effect of Luxembourg's free public transport policy on CO2 emissions from road transport. Data on the outcome variable, per capita CO2 emissions from the road transport sector, are constructed by combining spatial road transport CO2 emissions extracted from the European Emission Database for Global Atmospheric Research (EDGAR) v8 (Crippa et al., 2022) with population data from Eurostat's (2024) regional statistics. To control for other factors that may influence CO2 emissions from road transport, we include several covariates. Data on daily COVID-19 cases at the NUTS 2 level, used to account for the impact of lockdown measures, are sourced from Naqvi (2021). Data on working from home and commuting inflows, included to capture changes in mobility patterns due to the pandemic are obtained from a special extraction from the EU Labor Force Survey (EU-LFS).

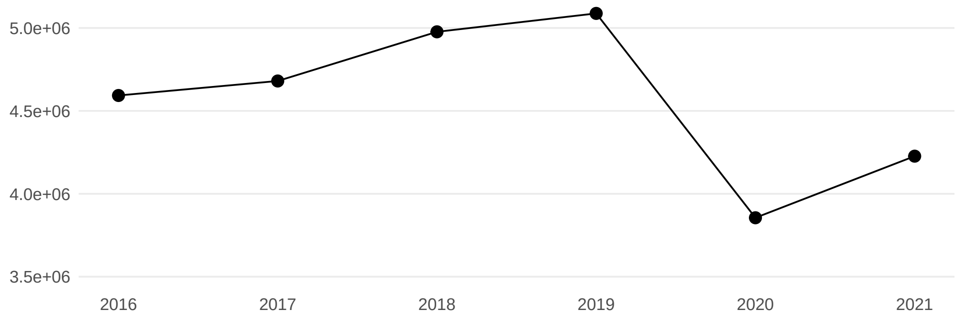
Fuel prices are sourced from the European Commission's (2024) weekly oil bulletin and included to control for the effect of prices. The electrification and energy efficiency of cars directly impact CO2 emissions from transport. To account for these effects, we include a control for the emission intensity of new passenger cars, which accounts for low-carbon engine technologies (EEA, 2024). This control captures the energy efficiencies of pure electric, hybrid, and alternate energy source vehicles. Data on loaded goods included to capture the effect of freight transport emissions are obtained from Eurostat's (2024) regional statistics. Finally, we use data on real GDP per capita from the regional statistics to control for overall differences in economic development. After dropping missing data to ensure a balanced panel, we are left with 136 regions over the sample period 2016-2021, giving a total of 816 region-year observations. The following subsections discuss in more detail the outcome variable, CO2 emissions from road transport, and the COVID-19 related controls used in our analysis.

3.1 CO2 emissions data

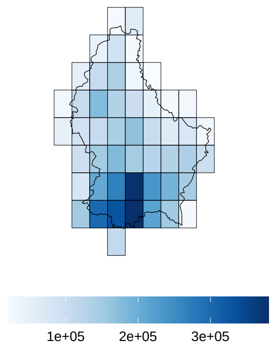
Road transport emissions are categorized under the Intergovenmental Panel for Climate Change (IPCC) 1996 sector category 1.A.3.b. Emissions are calculated as the product of fuel consumption times the associated IPCC emission factors. The EDGAR database provides annual sector specific grid maps expressed in ton substance with a spatial resolution of 0.1 degrees × 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).

Figure 2: Evolution of CO2 emissions in Luxembourg over time and space

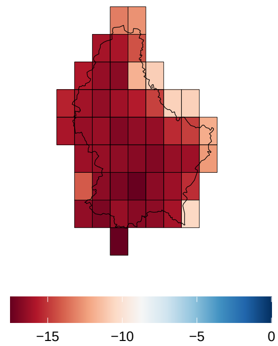
(a) Annual CO2 Emissions in Luxembourg



(b) Average Emissions 2016-2019



(c) % Change 2020-2021 vs. 2016-2019



Note: (a) Shows the time-series of annual emissions, while (b) and (c) display spatial distributions of emissions. (b) shows average emissions over the pre-treatment period, 2016-2019. (c) shows the percentage change from average emissions over the post-treatment period (2020-2021) compared to the pre-treatment period. 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.

We present the evolution of CO2 emissions from road transport for Luxembourg over time in Figure 2.[3] Panel (a) shows annual CO2 emissions from road transport over the period 2016-2021. The impact of COVID-19 can be seen in a drop in emissions from 2019 to 2020. Emissions in 2021 stay consistently below pre-pandemic levels. Panel (b) shows

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

the spatial distribution of average road transport emissions over the period 2016-2019, which constitutes our pre-treatment period. High emissions are indicated in dark blue and lower emissions in light blue. Emissions are concentrated around Luxembourg City and border regions with France. Panel (c) shows the percentage change of average post-treatment (2020-2021) emissions relative to average pre-treatment emissions. Emissions on average stayed below the pre-policy average in the entire country. The largest difference can be observed around Luxembourg City, while differences on the Eastern border of Luxembourg are less pronounced.

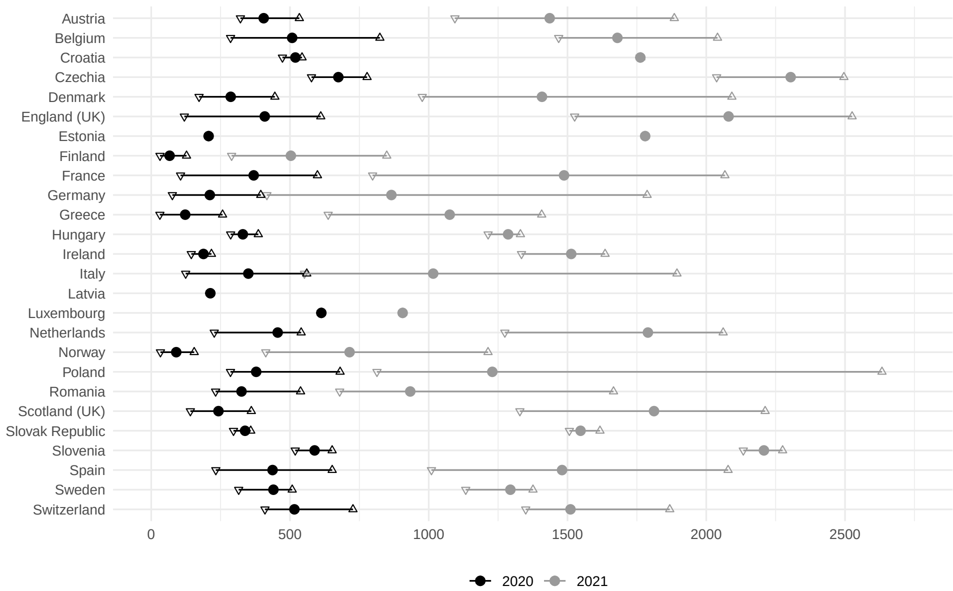
The reduction in CO2 emissions shown in Figure 2 is directly related to a reduction in fuel consumption, indicating a shift in mobility patterns. This shift may be attributed to various factors. Our primary interest is the causal effect of the free public transport policy. To discern this causal effect, we need to account for potential variation caused by other confounding effects. These potential sources of variation in CO2 emissions include COVID-19 related restrictions and reduced mobility, as well as an increase in the number people working from home and fewer commuting trips.

3.2 COVID-19 related variables

With the onset of the COVID-19 pandemic, many countries implemented lockdowns and travel restrictions to curtail the spread of the virus (Hale et al., 2021). Luxembourg was no exemption, with its government convening an extraordinary Government Council to respond to the pandemic, on the 12th of March 2020. Subsequently, mobility restrictions aimed at containing the spread of the virus came into effect on the 13th of March, 2020 (Government of the Grand Duchy of Luxembourg, 2020). The Our World in Data (OWID) COVID-19 Government policy stringency index, a composite index based on 9 response measures, illustrates that many countries, including Luxembourg, adopted similar measures during this period (Hale et al., 2021). These restrictions were often enforced at regional or local levels, triggered by the number of cases reported in specific areas. To capture the effect of the pandemic, we use data on confirmed COVID-19 cases as a proxy for various policy responses and reduced mobility.

This data is collected and reported by the COVID-19 European Regional Tracker at the NUTS 3 level (Naqvi, 2021). Information on the number of confirmed cases is taken from each country's official institutions responsible for providing COVID-19 related data. The regional data is then aggregated up to the country level and cross-checked against data from 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. The COVID-19 European Regional Tracker 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 in the COVID-19 European Regional Tracker to the NUTS 2 level.

Figure 3: Regional variation in COVID-19 cases for 2020 and 2021



Note: The average daily 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 NUTS 2 regions in other countries is taken from the COVID-19 European Regional Tracker (Naqvi, 2021).

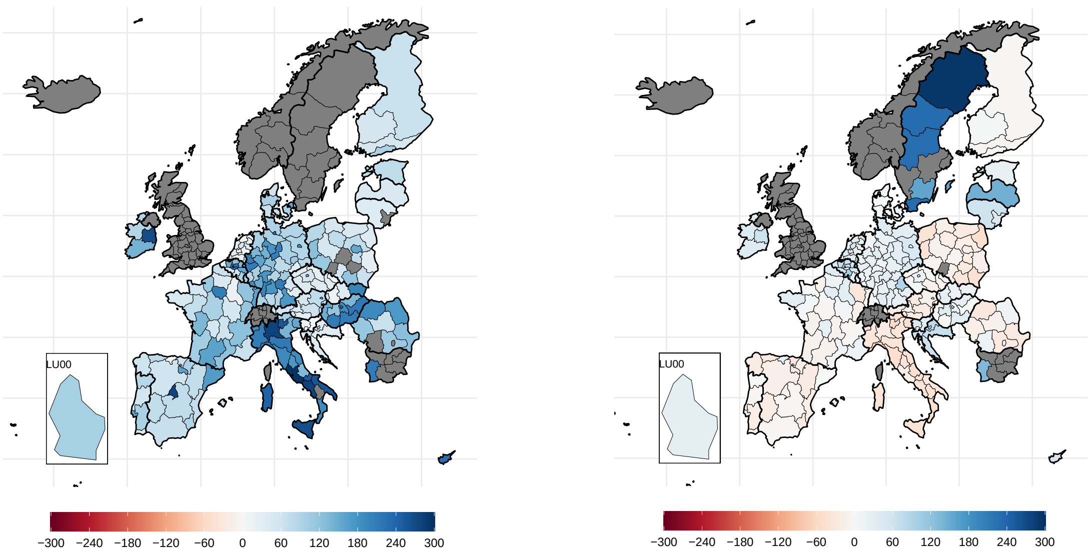
Figure 3 shows the average regional variation in the number of confirmed daily COVID-19 cases per 10,000 persons for 2020 and 2021. Dots represent the mean of confirmed cases at the NUTS 0 level (i.e., country level), the downward-facing triangle represents the NUTS 2 region with the lowest and the upward-facing 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. Average daily cases 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. Compared to country averages, we find only few comparable units to Luxembourg. At the regional level, however, we find several regions with more cases in 2020 and fewer ones in 2021, further motivating our usage of regional data.

We use data on working from home and commuting inflow to further address changes

Figure 4: Change (%) in persons usually working from home for NUTS2 regions

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



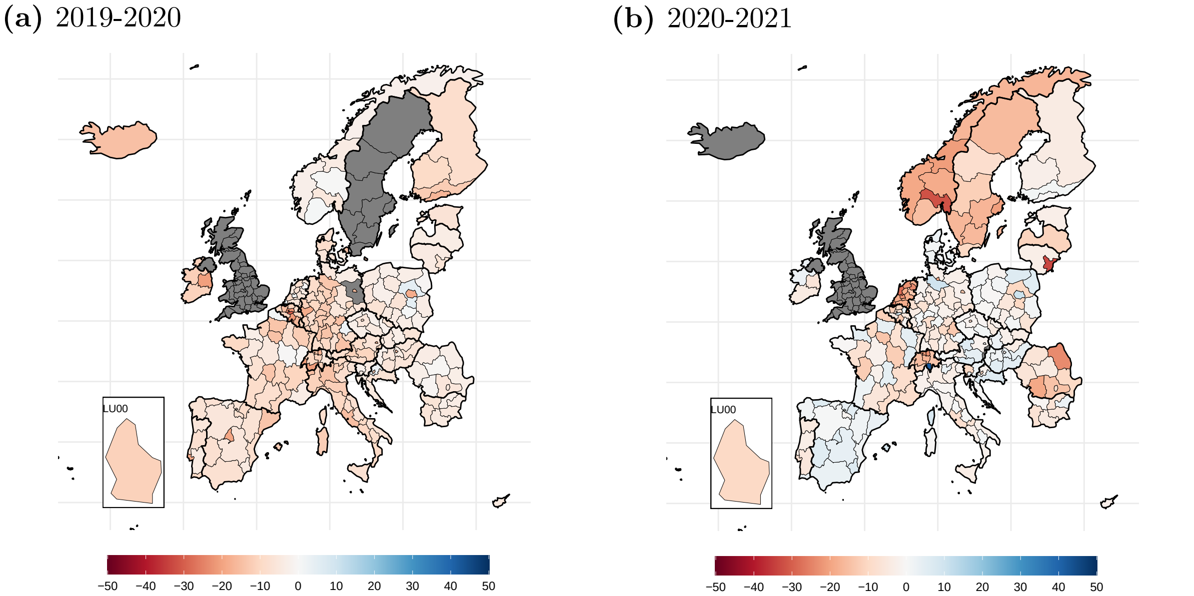
Note: Data is from a special extraction from the EU-LFS. Persons usually working from home with workplace at the NUTS 2 region shown in the figure and their location of residence in the associated country of the region.

in mobility behavior as a response to the pandemic. A person is classified as usually working from home 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 EU-LFS 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.[4] 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 4 shows yearly changes of persons usually working from home for NUTS 2 regions. Figure 4a 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 4b shows the change from 2020-2021. The map now shows a more nuanced picture. Some regions experienced a decrease in

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

Figure 5: Change (%) of persons never working from home for NUTS2 regions



Note: Data is from a special extraction from the EU-LFS. The figure shows yearly changes of persons never working at home for NUTS 2 regions which are the location of the workplace of these persons irrespective of their location of residence.

working from home, while some experienced another increase. Luxembourg is among the latter group and experienced a change of around +28%.

Figure 5 shows yearly changes of persons never working at home for NUTS 2 regions. Figure 5a shows percentage changes from 2020 to 2021. Overall, the map shows a decrease in persons never working from home, i.e. a decrease in commuters. This is to be expected since the pandemic caused an increase in working from home in most regions. Figure 5b 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.

4 Identification strategy

The inability to directly observe the potential outcomes of a specific unit both in the presence and in the absence of a policy event (treatment) complicates establishing causal relationships. In the case of Luxembourg, this translates to 'what would the CO2 emissions from road transport have been if the free public transport policy had not been introduced?" To overcome this problem, it is necessary to design an appropriate identification strategy that constructs a credible comparison group to serve as a counterfactual for Luxembourg after the policy's introduction.

Given that Luxembourg differs significantly from other EU countries in observable characteristics such as CO2 emissions per capita, GDP per capita, and motorization rates (refer to Section 2), we conduct our analysis at the NUTS 2 level. This approach is feasible because Luxembourg itself constitutes a NUTS 2 region, and it is likely that we can find more comparable units to construct the counterfactual for Luxembourg at the NUTS 2 regional level than at the country level. For instance, Berlin would probably serve as a better comparison to Luxembourg than Germany as a whole. However, even at a NUTS 2 level, Luxembourg records the highest per capita CO2 emissions from road transport (refer Table A). We therefore need an estimation strategy that can handle these complexities in our setting.

The canonical DID estimator calculates the difference in outcomes over time between treated and control units and relies on the parallel trends assumption. This assumption implies that, in the absence of treatment, the treated and control groups would have followed similar trends over time. By assuming parallel trends, the DID estimator controls for unobserved characteristics that remain constant over time, which might otherwise confound the results. Additionally, the DID method assumes that any time-varying shocks affecting the outcome are common to both treated and control groups, thereby isolating the treatment effect. However, the parallel trends assumption is often untestable, and in our specific setting, where Luxembourg already exhibits considerable differences in observable characteristics, we have reduced confidence that this assumption holds.

Some drawbacks of the DID method can be mitigated by the Synthetic Control (SC) method, which does not rely on the parallel trends assumption. Instead, the SC method creates a synthetic control unit as a weighted combination of units from the donor pool, ensuring that the pre-intervention outcomes of the synthetic unit closely match those of the treated unit. Importantly, not all units in the donor pool receive equal weights; higher weights are assigned to regions that are more similar to Luxembourg based on predictors of CO2 emissions (Abadie, 2021). The validity of the SC method depends on the trajectory of the outcome variable of the SC closely following that of the treated unit over a long pre-intervention period. This close alignment lends confidence that any deviations in outcome trends after the intervention can be attributed to the policy intervention. However, the substantial differences in predictors of CO2 emissions between Luxembourg and other units, coupled with Luxembourg's status as the country and even the NUTS 2 region with the highest per capita emissions, challenge the applicability of this method in our context.

Therefore, we employ the recently proposed estimation procedure, the SDID approach introduced by Arkhangelsky et al. (2021). SDID combines the strengths of both DID and SC methods and circumvents the common drawbacks associated with traditional DID and SC methods. Specifically, it overcomes the challenge of estimating causal relationships when parallel trends are unlikely to hold in aggregate data for DID and eliminates the necessity for the treated unit to be within the convex hull of control units for SC. SDID essentially constructs a synthetic parallel trend in for Luxembourg. Section 5 discusses the SDID estimation procedure in detail.

Identification is further complicated by the COVID-19 pandemic coinciding with the policy's introduction. Since the pandemic was a global shock affecting all regions, its effects should not technically bias our analysis, as both the treated and control units were similarly exposed. However, regions adopted varying measures and policies to limit the spread of the virus, which could have differential impacts on mobility across regions. For instance, a higher number of COVID-19 cases may lead to shifts toward remote working, online education, and changes in consumer behavior. These policy responses, potentially influenced by the number of cases, could correlate with regional mobility restrictions. To account for these factors, we control for regional average daily COVID-19 cases across NUTS 2 regions.

Mobility patterns may have also shifted due to the pandemic. This is again only problematic insofar as regions experienced such shift differently form one another. These changes include individuals who did not work from home prior to the pandemic but began and continued doing so after the COVID-19 outbreak. Consequently, mobility within countries (and within regions) and commuting patterns across borders might have changed. However, as discussed in detail in Section 3.2, Luxembourg did not experience particularly significant 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.

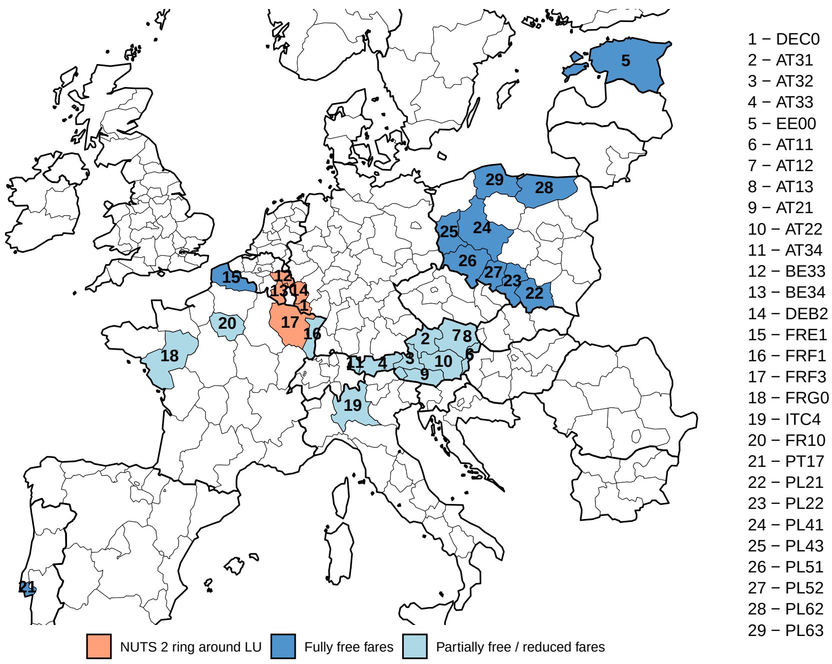
Finally, to avoid bad comparisons with already treated units, we excluded NUTS 2 regions that introduced free fares during our sample period. We drop the following regions before estimating our main results. Estonia (EE) introduced free public transport in Tallin in 2013 and further extended it in 2017. Given that Estonia is in itself a NUTS 2 region, we drop the whole country. Dunkirk and Calais in France introduced free public transport for all passengers in 2018 and 2020, respectively. Both are located within the same NUTS 2 region (FRE1) that we drop. We also drop Cascais in Portugal (PT17), which introduced free fares in 2020.

Several municipalities in Poland introduced some form of free public transport schemes during our sample period. Štraub et al. (2023) chart the spatial distribution of these policies in Poland, which covers over 90 free-fare programs since 2007. Polish municipalities that introduced free fares for everybody during our sample period cover 12 NUTS 2 regions which we drop (PL11, PL12, PL21, PL22, PL31, PL34, PL41, PL43, PL51, PL52, PL62, PL63). We also exclude the NUTS 2 regions surrounding Luxembourg to control for possible spillover effects. These regions include the Province of Luxembourg (BE34) and the Province of Liege (BE33) in Belgium, Trier (DEB2), and Saarland (DCE0) in Germany, and Lorraine in France (FRF3).

As a robustness check, we additionally drop regions that introduced free fares for specific groups (e.g., students, residents, elderly, etc.) or subsidized public transport during our sample period. These cases can distort the estimated effect if these policies significantly shifted the modal split in favor of public transport systems. Regions we drop in our robustness checks include the following. Attica in Greece (EL30), and Nantes (FRG0), Strasbourg (FRF1), and Paris (FR10) in France. These regions all introduced some form of free public transport for residents and/or students (Fare free public transport, 2024). Austria (AT) 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.

The different regions that we drop in our main specification as well as in the robustness checks are shown in Figure 6. The figure zooms in on NUTS 2 regions in Europe to highlight potentially bad controls. NUTS 2 regions that introduced free fares for all passengers during our sample period are shown in darker blue. These are all the regions we drop in our specification to obtain our main results. Those that introduced free fares for specific groups only or introduced reduced fares are shown in lighter blue. These regions are additionally excluded from our sample in a robustness check. The NUTS 2 ring around Luxembourg is shown in orange and is dropped in all specifications.

Figure 6: NUTS 2 regions - bad controls



Note: NUTS 2 regions that are potential bad control are highlighted. The figure zooms in on NUTS 2 regions in Europe to better visualize regions that we intentionally drop in the analyses. Not all uncolored regions are necessarily in the donor due to missing observations for some regions and countries.

5 Synthetic difference-in-differences (SDID)

We use the SDID methodology to estimate 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 ATT without relying on parallel pre-treatment trends between treated and not-treated units. 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 Euclidean 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 the procedure 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, DID approaches use an unweighted two-way fixed-effects regression, thus relying on parrallel pre-treatment trends in aggregate data. 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.

5.1 Handling covariates

We follow the procedure for handling covariates outlined in Arkhangelsky et al. (2021) and refined in Clarke et al. (2023). 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 in the 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 daily COVID cases, the number of commuters, and the number of persons usually working from home, fuel prices, freight transportation, and GDP per capita. 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 is then applied to the adjusted outcome variable.

5.2 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 analysis, which enables 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 denoted as d_t and given by:

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

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 units. 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). They are given by:

$$\bar{Y}_{base}^1 = \sum_{t=1}^{T_{pre}} \hat{\lambda}_t^{sdid} \bar{Y}_t^1, \tag{7}$$

and

$$\bar{Y}_{base}^0 = \sum_{t=1}^{T_{pre}} \hat{\lambda}_t^{sdid} \bar{Y}_t^0, \tag{8}$$

where the time weights, $\hat{\lambda}_t^{sdid}$, come from equation (3).

Confidence bands around the estimated d_t's are generated with a placebo-based approach in the following sequence:

(i) Exclude the treated unit (in our case Luxembourg) from the sample

(ii) Randomly assign treatment to a unit (from the remaining units, which are all controls units)

(iii) Calculate the outcome adjusted for covariates following equations (4) and (5)

(iv) Compute equation (6) and store the result

(v) Repeat 2-4 many times (e.g., 1,000 times)

(vi) Obtain the 5% quantile from the sample distribution of the stored results for each time period t.

Note that in the case the SDID estimation includes covariates, the outcome has to be newly adjusted every time treatment is assigned to a random unit. This is necessary because equation (4) estimates the coefficients of the covariates based on the sample of not-treated units. This sample slightly changes each time treatment is re-assigned.

6 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 6.1. These include models without any covariates, one with COVID-related covariates, and one with a set of additional controls; the latter being our main specification. Section 6.2 tests the robustness of the main results. These checks include in-time placebo tests, specifications that exclude some of our controls, fuel-tourism effects, as well as results from a restricted sample. We find that our results are robust against these checks.

6.1 Results

We provide results for three different model specifications. The first one does not adjust emissions for covariates; it is based on equation (1). The second specification adjusts the outcome variable for COVID-19 related covariates as described in Section 5.1. The auxiliary regression is given by:

$$\begin{aligned} log(CO2/cap)_{it}^{co} =& \alpha_i + \gamma_t + \beta_1 asinh(cases)_{it}^{co} + \beta_2 asinh(nvrwfh)_{it}^{co} + \\ & \beta_3 asinh(wfh)_{it}^{co} + u_{it}, \end{aligned} \tag{9}$$

where the outcome variable is the log of road transport CO2 emission per capita. It is regressed on the inverse hyperbolic sine ($asinh$) of COVID $cases$, on people usually working from home (wfh) with their work-place location in the associated NUTS 2 region, and on people never working from home ($nvrwfh$) with their work-place location in the associated NUTS 2 region. 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. This allows us to interpret the estimated coefficients as elasticities under certain assumptions.[5]

[5]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

The third specification is our main specification and adjusts the outcome variable for additional covariates and is given by:

$$\begin{aligned} log(CO2/cap)_{it}^{co} =& \alpha_i + \gamma_t + \beta_1 asinh(cases)_{it}^{co} + \beta_2 asinh(nvrwfh)_{it}^{co} + \\ & \beta_3 asinh(wfh)_{it}^{co} + \beta_4 log(gdp)_{it}^{co} + \beta_5 log(ei)_{it}^{co} + \\ & \beta_6 diesel_{it}^{co} + \beta_7 petrol_{it}^{co} + \beta_8 log(frt)_{it}^{co} + u_{it}. \end{aligned} \tag{10}$$

The set of covariates that we consider in this specification additionally includes: the log of real GDP per capita, (gdp), and energy intensity, (ei), measured as average CO2 emissions of newly registered vehicles, ($diesel$), diesel, and ($petrol$), petrol prices in real terms (adjusted with the harmonized index of consumer prices - HICP) to capture cross-unit variations in fuel prices, (frt), log of freight transport, measured as tons of goods loaded in the region, to control for changes in freight transport. Estimation results for the auxiliary regressions based on Specifications (9) and (10) are shown in Table B.1 in Appendix B.

We provide estimates of the ATTs for the periods that the treatment is in effect, i.e., 2020-2021, as well as an event-study analysis over the period 2016-2021 in Figure 7 for the three different specifications. Estimates for the ATTs are shown in Figure 7a and the event-study estimates are shown in Figure 7b. 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 CCOVID-19 related covariates - only COVID covariates, and 3) adjusting for the full set of covariates - all covariates. The latter specification produces our main results. The time weights for this variant are assigned to 2017 and 2019 with weights of 0.74 and 0.26, respectively. Figure 7b shows no statistically significant violation of pre-treatment trends.

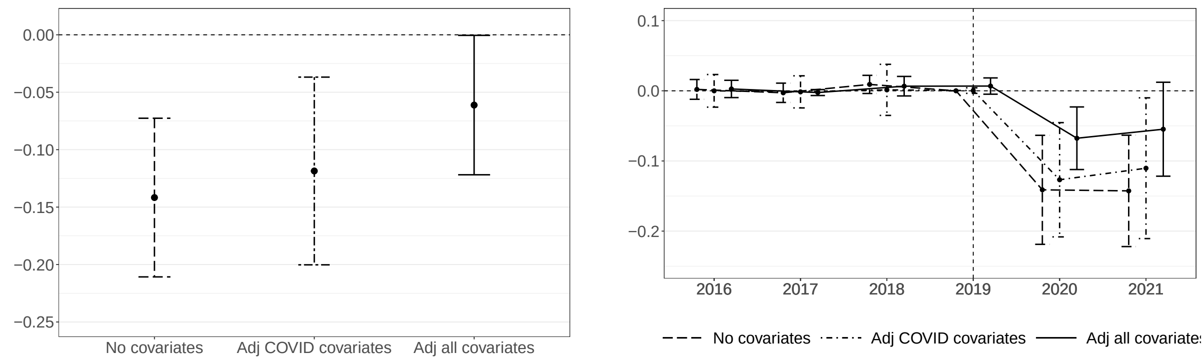
The estimated ATTs for the specification including all covariates indicate an effect at around -0.061, i.e., a 6.1% reduction in transport CO2 emissions as a response to the free-public transport policy implemented in March 2020. This is less in magnitude compared to controlling only for COVID-19 related covariates, which yields an estimated ATT of around -11.8%. The specification with no covariates provides the largest 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. This also indicates that the tram extension in 2017 did not significantly alter Luxembourg's emissions trajectory compared to our synthetic control. Post-treatment effects show statistical significance in 2020 for all three specifications. In 2021, the confidence intervals based the specifications that adjusts the outcome variable for all covariates slightly cross the dashed zero-line at the 5% significance level.

The control units that contribute to the synthetic control together with their respec-

provides stable elasticities. The reported coefficients appear to be robust in our specifications.

Figure 7: ATTs and event study estimates

(a) ATTs since treatment in 2020 **(b)** Event study estimates for 2016-2021



Note: ATTs and event study estimates of the 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. The following NUTS 2 regions are dropped from the donor pool: NUTS 2 ring around Luxembourg, regions that introduced free public transport for all passengers during our sample period.

tive weights for the third specification are graphically shown in Figure C.1 in Appendix C. The regions with the largest weights come from Belgium, Denmark, Spain, Hungary, Italy, and Poland. Regions from the Netherlands also receive sizable weights. Czechia, Finland, France, and Slovakia enter the synthetic control with smaller weights and only 1-2 regions each. 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 presents the realizations of pre-treatment control variables for 2019. Belgium, Denmark, 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. 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, essentially creating a synthetic parallel trend. These trends do not necessitate that the magnitude of controls match well but rather focus on their trends before treatment.

Figure C.2 in Appendix C shows how well the SDID estimation aligns pre-treatment trends for Luxembourg and its synthetic control. Luxembourg is shown as a solid line and the weighted average across control regions according to the assigned SDID unit weights as a dashed line. The figure also shows two additional averages over different groups of control regions. These include the average pre-treatment trend in the adjusted outcome variable over all regions and the unweighted average over regions that received a positive weight. Figure **??** shows the absolute level of trends, while Figure **??** standardizes the trends so that they are visually more easily comparable.[6]

The absolutes levels of the adjusted outcome differs markedly between Luxembourg and the different controls. This reinforces our argument that the SDID procedure is preferable over standard DID and SC methods because it does not assume similar absolute values in any steps of its procedure. We can see from the standardized trends in part b of the figure 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 that the SDID assigns unit weights to create a synthetic parallel trend to Luxembourg compared to a simple average of NUTS 2 regions.

6.2 Robustness

In this sub-section, we run a set of robustness tests to assess the sensitivity of our main results. Overall, the robustness checks confirm the stability and reliability of our main findings. They include sensitivity analyses across different model specifications, an in-time placebo test, an analysis using a restricted donor sample, and the inclusion of relative fuel prices. They all yield consistent results, strengthening the validity of our conclusions and provide further evidence that our estimated effects are not driven by model specification choices or sample selection biases, lending credibility to our estimation results. The robustness checks are outlined in some detail below.

In-time placebo: We perform an in-time placebo (also referred to as back-dating test) as suggested by Abadie (2021). In this test, we assign the free public transport policy to 2019, the year before its actual introduction. Since the treatment is artificially assigned to a date prior to the treatment we should not observe a significant post-placebo treatment effect. Figure D.1 in Appendix D shows the results of this exercise. The solid black line represents our main specification with all covariates, and the dot-dash line represents the specification without covariates. We do not estimate the specification adjusted only for COVID-19 covariates since the policy is back-dated before the pandemic. The confidence bands at the 5%-significance level clearly encompass the zero line, indicating no significant treatment effect in 2019. The absence of a post-placebo treatment effect provides further validation for our estimated results.

Restricted sample: We also conduct our analysis on a more restricted donor sample to further test the robustness of our results. In this analysis, we exclude regions that introduced any form of public transport subsidy affecting specific segments of the population, as described in Section 3. We additionally exclude Torrevieja in Spain, Livi-

[6]Standardization is performed by subtracting the mean and dividing by the standard deviation within each group.

gno in Italy, Attica in Greece, and Nantes, Strasbourg, and Paris in France, all of which introduced some form of free public transport for residents and/or students (Fare free public transport, 2024). We also exclude all Austrian regions due to the nationwide climate ticket introduced in 2021, which increased accessibility and significantly reduced prices for comparable tickets. The results of our analysis using this restricted sample are reported in Figure D.2 in Appendix D. Part (a) of the figure shows the estimated ATTs of our three specifications. The specification that includes all covariate adjustments estimates the ATT at -0.06, statistically identical to our main results. Part (b) of the figure shows the corresponding event-studies. Again, the trajectories and confidence bands are visually indistinguishable from the ones based on the larger sample.

Alternative specifications: To further assess the robustness of our main results shown in Figure 7, we test their sensitivity to a set of alternative model specifications. Given that our measures for people working from home and those commuting to work likely capture similar dynamics[7] to a certain degree, we test the sensitivity of our results by excluding one or the other from our specifications. Additionally, Table B.1 shows that the coefficient for $log(frt)$ (log of freight transport) is statistically insignificant. Consequently, we estimate the following specifications, each excluding different combinations of these covariates: a model excluding controls for freight transport (Spec 1), a model omitting controls for working from home (Spec 2), a model excluding both freight transport and working from home (Spec 3), a model excluding the commuting variable, $nvrwfh$ (Spec 4), and a model excluding both the commuting variable and freight transport (Spec 5). The results of these sensitivity analyses are displayed in Figure D.3 and Table D.1 in Appendix D. All five alternative specifications yield estimates similar to our main specification, with the estimated ATTs slightly below our main specification's estimate of approximately -6.1%. The consistency of the estimates across these five different model specifications underscores the robustness of our findings and confirms their reliability to the inclusion or exclusion of various controls.

Fuel tourism: We now turn to a brief discussion on fuel tourism. Luxembourg typically enjoys lower fuel prices than its neighbouring regions, which makes it susceptible for fuel tourism. This leads to higher fuel consumption within Luxembourg, subsequently increasing transport emissions captured in EDGAR. Therefore, an increase in fuel prices in Luxembourg, relative to its neighbouring regions could reduce fuel tourism and thus emissions. This effect would be unrelated to the free public transport policy and confound our estimates. We already control for absolute fuel prices in our main specification, which should capture this effect to some degree. Arguably fuel tourism is more adequately accounted for by fuel prices of Luxembourg relative to its neighbours. We now examine, how well the fuel tourism effect is captured by fuel prices in absolute terms in our model. Figure D.4 in Appendix D compares both absolute and relative fuel prices between Lux-

[7] They show a moderate correlation of around 0.6.

embourg and its neighbouring regions. Throughout our sample period, Luxembourg's absolute fuel prices are consistently lower than those of its neighbours, resulting in relative prices below one. While relative prices compared to Germany remain fairly stable, they increase relative to Belgian and French regions in 2020, potentially discouraging fuel tourism and reducing fuel consumption in Luxembourg.

To test the robustness of our estimates, we re-estimate our main specification incorporating relative fuel prices, calculated as the fuel price of a NUTS 2 region relative to the mean of its neighbours that are not part of the same country, as an additional control. The estimated ATT is -0.0604 and is statistically indistinguishable from our main result (-0.0612). Similarly, the event-study estimates align closely with our main results. We attribute this consistency to several factors. First, absolute fuel prices may partly reflect the effects of relative prices. Second, the relative fuel price in Luxembourg remained below one throughout the sample period, maintaining an incentive for fuel tourism. Third (and arguably most importantly), the estimated ATT is based on a comparison between weighted averages of the pre-and post-treatment periods. As shown in Table D.2 in Appendix D, there is no significant difference between these weighted averages for diesel and petrol prices in Luxembourg relative to its neighbors. This finding suggests that the SDID estimation effectively captures regions and time periods that are comparable and robust to observed changes in relative fuel prices.

7 Discussion

We now discuss the estimated effect size of Luxembourg's free public transport policy, implemented in 2020, on CO2 emissions from road transport. We attribute the estimated ATT of -6.1% to a modal shift from private motorized transport to public transport and ask whether this estimated effect size is reasonable. Some may perceive 6.1% reduction as modest, considering the comprehensive nature of the policy. Conversely, others might argue that this effect is disproportionately large given the existing modal split in Luxembourg, where public transport accounts for approximately 15% of journeys and private vehicles dominate with around 80% (we will return to this issue in more detail below). Therefore, to evaluate the plausibility of our estimate, we employ a back-of-the-envelope calculation from two perspectives: first by looking at changes in car traffic, and second by looking at increases in the use of public transport.

We begin by examining traffic count data from Luxembourg's open data portal (Gouvernement du Grand-Duché de Luxembourg, 2023). Recall that Figure 1 maps traffic posts in Luxembourg. We compute the total bi-directional car traffic volume reported across all the traffic posts. This volume increased by around 7% in 2019 relative to 2018. Assuming this upward trend in car travel would have continued, the free public transport policy should then reduce, if not entirely negate, this growth. Indeed, travel volume almost stagnated from 2019-2021 with a slight decrease of -0.4%. However, it is essential to account for the impact of COVID-19-related travel restrictions, which drastically reduced mobility in 2020. In Luxembourg, we observe a sharp decline in car travel of around 10% in 2020, likely due to the immediate effects of pandemic restrictions. The subsequent year, 2021 experienced an 11% rebound in car travel, almost mirroring the decline observed in 2020. This pattern suggests a transient impact of the pandemic on car travel behavior.

Next, we resort to changes in public transport usage of the tram, where usage data is available, to further examine the compatibility of our estimates. Consider the following back-of-the-envelop calculation. Following Bigi et al. (2023), we assume a modal split where private vehicles account for 80% and public transport for 15% of total transport. We further assume that the observed reduction in CO2 emissions results from a modal shift from private vehicles to public transport. A 6.1% reduction in CO2 emissions from road transport then implies a corresponding decrease in private vehicle usage by approximately 4.88%. This decrease is derived from the fact that private vehicles represent 80% of the modal split and thus contribute the majority of emissions reductions (calculated as 80% of the 6.1% reduction). To maintain the overall transport capacity, public transport usage must increase by approximately 33%, calculated by dividing the reduction in private vehicle usage (4.88%) by the initial share of public transport (15%).

To assess the credibility of this effect size, we utilize data on the average daily number of people using trams on weekdays from the 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 16% and 47% from 2020-2021 and 2021-2022, respectively. These numbers align with our estimates, suggesting that our effect size is reasonable. Additionally, we can relate these results to the LUXmobile survey, conducted by the Luxembourg City Council (Luxmobile, 2020). This survey reports 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. While the descriptive analysis does not direclty validate the causal estimates, the observed figures are consistent with our estimated effect size, lending further credibility to our findings.

Finally, we calculate the associated marginal abatement cost of carbon for the policy as the government expenditure per ton of CO2 abated. A simple calculation takes the foregone revenue from ticket sales of around 41 Mio. Euros and compares it to the tons of CO2 emissions abated according to our estimates. The latter are calculated as the counterfactual post-treatment emissions for Luxembourg: $\frac{1}{T_{post}} \sum_{t=T_{pre}+1}^{T} CO2_t^{tr} / (1 - \hat{\tau})$, where tr indicates the treated unit. With this back-of-the-envelop calculation, we estimate a marginal abatement cost of EUR 156 per ton of carbon. This is, of course, a crude estimate and does not capture the full costs nor the additional non-CO2-benefits of the policy. As Hahn et al. (2024) argue, such calculations overlook the benefits to inframarginal individuals—those who do not alter their behavior in response to the policy—thereby potentially underestimating the policy's overall effectiveness. They suggest a more comprehensive approach, the Marginal Value of Public Funds (MVPF) framework, which captures these benefits and provides a more accurate assessment of the policy's impact. We leave such detailed calculations to future research.

8 Conclusion

In this paper, we estimate the causal effect of Luxembourg's free public transport policy introduced in 2020 on road transport emissions. Our findings indicate an estimated effect of approximately -0.061, corresponding to a reduction in road transport CO_2 emissions of around 6.1%. The effect remains robust across a range of model specifications that account for factors such as the COVID-19 pandemic, fuel prices, the prevalence of remote working, and commuting patterns. Additional robustness tests, including in-time placebo tests, sample restrictions, and fuel tourism further corroborate our main findings. Our results align with the descriptive evidence from traffic volume data and the evidence from the LUXmobile survey, which show an increase in public transport use as a result of the free public transport policy. The consistency of these results supports the conclusion that the policy had a statistically significant causal effect, indicating a behavioral shift from private car use to public transport.

Our findings are of high policy relevance. The reduction in CO_2 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 CO_2 emissions and fostering a sustainable future.

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)	
	Coef.	SE	Coef.	SE
asinh(cases)	−0.0284***	(0.0049)	−0.0119	(0.0072)
asinh(nvrwfh)	0.0789***	(0.0264)	0.1217**	(0.0480)
asinh(wfh)	−0.0148**	(0.0062)	−0.0459***	(0.0101)
log(gdp)	0.3613***	(0.0731)		
log(ei)	0.2219***	(0.0418)		
diesel	−0.7463***	(0.0919)		
petrol	0.2765**	(0.113)		
log(frt)	0.0148	(0.0097)		
Obs	816		816	
N	136		136	

Note: 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

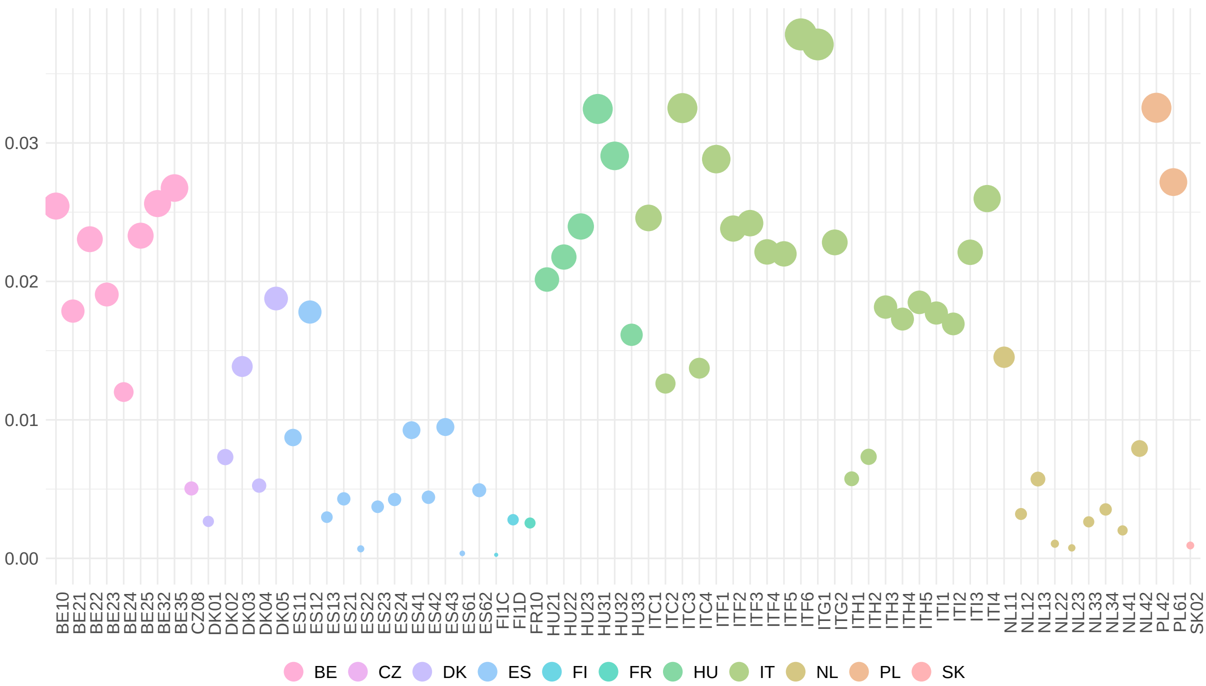


Table C.1: Summary values of selected variables in 2019 of NUTS 2 regions that received positive weights

NUTS2	Name	Weights	CO2pc	GDPpc	EI	NvrWFH	WFH	Diesel	Petrol
LU00	**Luxembourg**	-	8.2879	78700	133.0	348.67	33.90	1.0387	1.1432
ITF6	Calabria	.0378393	1.5686	17700	119.4	512.71	14.87	1.4324	1.5237
ITG1	Sicilia	.0371127	1.3241	18400	119.4	1284.27	31.61	1.4324	1.5237
PL42	Zachodniopomorskie	.0325411	1.7336	19000	130.4	600.91	31.09	1.1201	1.1095
ITC3	Liguria	.032517	1.1649	32900	119.4	582.16	28.68	1.4324	1.5237
HU31	Észak-Magyarország	.0324565	1.6624	15100	129.7	426.95	4.25	1.1198	1.0703
HU32	Észak-Alföld	.029067	1.4100	14700	129.7	593.31	4.62	1.1198	1.0703
ITF1	Abruzzo	.0288337	2.4989	25700	119.4	466.53	19.18	1.4324	1.5237
PL61	Kujawsko-pomorskie	.0271732	1.7620	18200	130.4	713.43	33.88	1.1201	1.1095
BE35	Prov. Namur	.0267455	3.8722	24500	121.5	125.37	14.52	1.3334	1.2908
ITI4	Lazio	.0259829	1.0559	35200	119.4	2285.14	102.91	1.4324	1.5237
BE32	Prov. Hainaut	.0256232	2.3871	22800	121.5	322.54	37.43	1.3334	1.2908
BE10	Rég. de Bruxelles-Capitale	.0254423	0.4279	63400	121.5	483.18	31.07	1.3334	1.2908
ITC1	Piemonte	.024585	1.9573	32000	119.4	1707.21	75.30	1.4324	1.5237
ITF3	Campania	.0242078	0.7966	19500	119.4	1519.75	42.20	1.4324	1.5237
HU23	Dél-Dunántúl	.0239685	2.2659	15500	129.7	338.67	3.98	1.1198	1.0703
ITF2	Molise	.0238194	3.3549	21900	119.4	101.97	2.38	1.4324	1.5237
BE25	Prov. West-Vlaanderen	.0233038	2.0159	35700	121.5	375.18	50.19	1.3334	1.2908
BE22	Prov. Limburg (BE)	.0230481	2.4709	29700	121.5	248.93	21.71	1.3334	1.2908
ITG2	Sardegna	.022819	2.5616	22000	119.4	561.49	16.29	1.4324	1.5237
ITF4	Puglia	.0221319	1.0517	19600	119.4	1167.69	25.65	1.4324	1.5237
ITI3	Marche	.0221046	1.7500	28400	119.4	597.78	19.14	1.4324	1.5237
ITF5	Basilicata	.0219905	2.9963	23300	119.4	188.59	4.19	1.4324	1.5237
HU22	Nyugat-Dunántúl	.0217611	1.9203	22200	129.7	438.74	4.25	1.1198	1.0703
HU21	Közép-Dunántúl	.0201367	1.9231	21100	129.7	453.53	3.48	1.1198	1.0703
BE23	Prov. Oost-Vlaanderen	.0190552	1.8888	33500	121.5	478.84	48.61	1.3334	1.2908
DK05	Nordjylland	.0187648	2.3619	32900	111.9	199.54	21.74	1.3608	1.5686
ITH5	Emilia-Romagna	.0184892	1.9062	36600	119.4	1950.99	84.01	1.4324	1.5237
ITH3	Veneto	.0181474	1.7508	34200	119.4	2043.72	88.04	1.4324	1.5237
BE21	Prov. Antwerpen	.0178575	1.4795	43400	121.5	573.01	54.58	1.3334	1.2908
ES12	Principado de Asturias	.0177897	2.0848	25000	121.3	337.11	25.69	1.1645	1.2443
ITI1	Toscana	.0177173	1.6780	33100	119.4	1521.73	67.87	1.4324	1.5237
ITH4	Friuli-Venezia Giulia	.0172797	2.4731	32700	119.4	481.83	24.46	1.4324	1.5237
ITI2	Umbria	.0169312	1.9201	26600	119.4	336.74	12.90	1.4324	1.5237
HU33	Dél-Alföld	.016146	1.6012	16500	129.7	534.09	3.24	1.1198	1.0703
NL11	Groningen	.0145252	1.4295	36000	98.4	185.30	38.05	1.2825	1.5581
DK03	Syddanmark	.0138564	2.1226	35300	111.9	412.18	46.22	1.3608	1.5686
ITC4	Lombardia	.0137334	0.9765	39900	119.4	4252.88	173.33	1.4324	1.5237
ITC2	Valle d'Aosta	.0126263	4.8063	39000	119.4	57.96	1.90	1.4324	1.5237
BE24	Prov. Vlaams-Brabant	.0120106	2.0686	39900	121.5	323.36	30.61	1.3334	1.2908
ES43	Extremadura	.009485	3.3205	20700	121.3	353.45	19.64	1.1645	1.2443
ES41	Castilla y León	.0092571	4.7266	26800	121.3	888.02	47.45	1.1645	1.2443
ES11	Galicia	.0087266	2.1530	25600	121.3	975.87	59.90	1.1645	1.2443
NL42	Limburg (NL)	.0079331	1.8820	35000	98.4	384.30	68.80	1.2825	1.5581
ITH2	Prov. Auton. di Trento	.0073333	2.6529	39600	119.4	225.23	8.63	1.4324	1.5237
DK02	Sjælland	.0073143	2.2742	27500	111.9	228.76	29.58	1.3608	1.5686
ITH1	Prov. Auton. di Bolzano	.0057474	2.8928	48700	119.4	249.26	15.82	1.4324	1.5237
NL13	Drenthe	.0057257	3.0915	27000	98.4	163.22	32.62	1.2825	1.5581
DK04	Midtjylland	.0052543	1.9565	36400	111.9	461.50	52.48	1.3608	1.5686
CZ08	Moravskoslezsko	.0050482	1.4662	22800	128.7	529.36	25.00	1.1444	1.1520
ES62	Región de Murcia	.0049217	1.7941	23300	121.3	549.35	25.37	1.1645	1.2443
ES42	Castilla-La Mancha	.0044123	4.4251	22400	121.3	688.99	36.92	1.1645	1.2443
ES21	País Vasco	.0042974	1.1363	36500	121.3	869.33	39.64	1.1645	1.2443

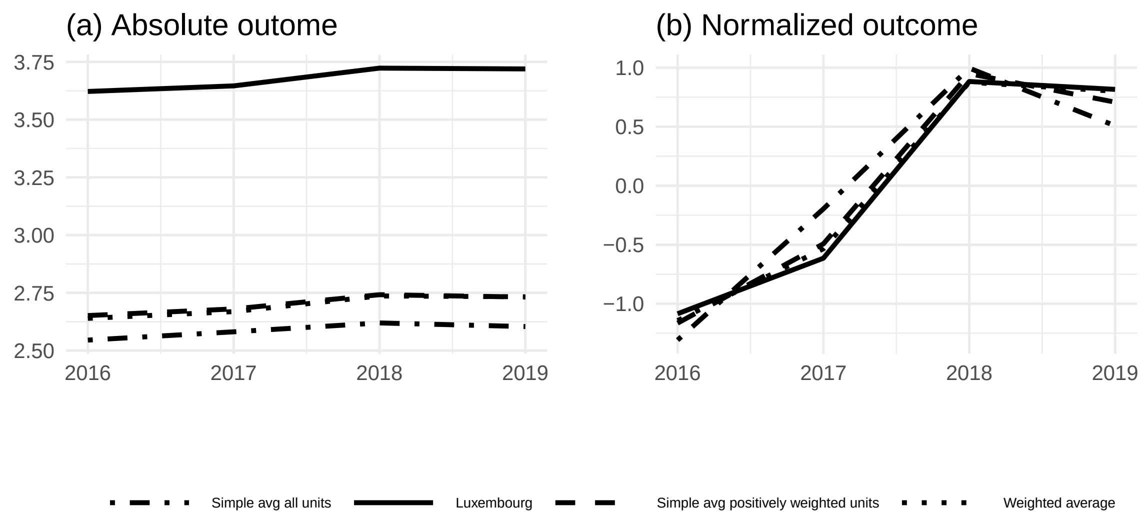
Continued on next page

Table C.1 continued from previous page

NUTS2	Name	Weights	CO2pc	GDPpc	EI	NvrWFH	WFH	Diesel	Petrol
ES24	Aragón	.0042491	3.3303	30900	121.3	533.90	28.94	1.1645	1.2443
ES23	La Rioja	.0037282	2.9902	30200	121.3	124.94	4.94	1.1645	1.2443
NL34	Zeeland	.0035329	1.6308	31500	98.4	123.80	30.61	1.2825	1.5581
NL12	Friesland (NL)	.0032041	2.6128	27700	98.4	235.10	42.09	1.2825	1.5581
ES13	Cantabria	.0029762	2.0262	26200	121.3	209.55	11.44	1.1645	1.2443
FI1D	Pohjois- ja Itä-Suomi	.0027892	3.3077	28300	115.3	411.31	58.80	1.3593	1.4714
DK01	Hovedstaden	.0026687	0.6252	50900	111.9	651.72	86.50	1.3608	1.5686
NL33	Zuid-Holland	.0026372	1.1515	38400	98.4	1111.51	247.64	1.2825	1.5581
FR10	Ile-de-France	.0025525	0.5824	56700	113.8	4075.87	412.68	1.3708	1.4339
NL41	Noord-Brabant	.0020182	1.8294	40200	98.4	869.95	184.98	1.2825	1.5581
NL22	Gelderland	.0010571	2.0042	33500	98.4	656.29	173.67	1.2825	1.5581
SK02	Západné Slovensko	.0009302	1.3858	20500	130.4	723.61	40.52	1.1556	1.2464
NL23	Flevoland	.0007569	2.4235	29300	98.4	113.30	24.36	1.2825	1.5581
ES22	Comun. Foral de Navarra	.0006879	2.5927	34400	121.3	271.50	11.67	1.1645	1.2443
ES61	Andalucía	.0003595	1.2590	21000	121.3	2805.20	149.95	1.1645	1.2443
FI1C	Etelä-Suomi	.0002549	1.5876	30300	115.3	360.17	72.31	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. *NvrWFH* refers to all persons never working from home in a NUTS2 region regardless of their region of residence. *WFH* is the number of of persons usually working from home in a NUTS2 region with the residency in the same country. *Diesel* is the annual average real price of diesel. *Petrol* is the annual average real price of petrol. All values are for 2019.

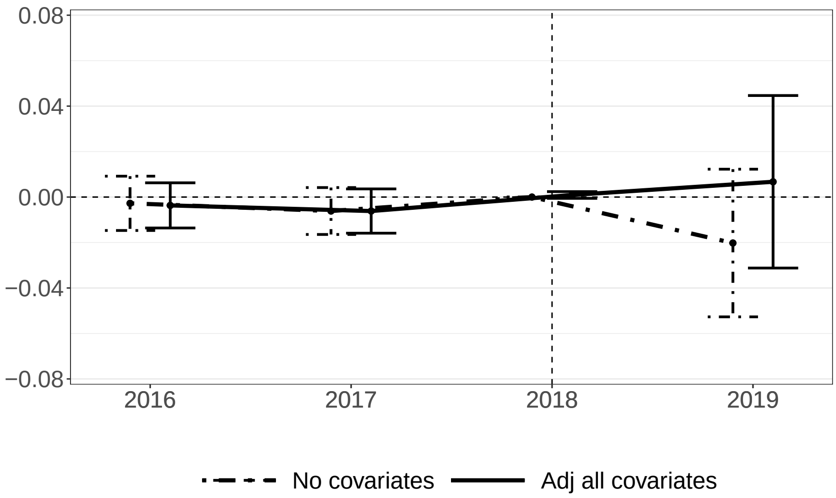
Figure C.2: Pre-treatment trends of the adjusted log CO2 per capita emissions



Note: *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 positive weights.

Appendix D

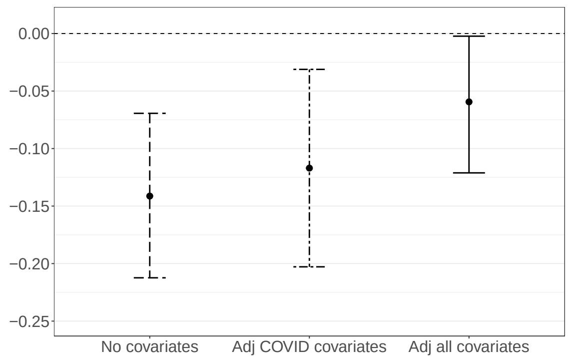
Figure D.1: In-time placebo test



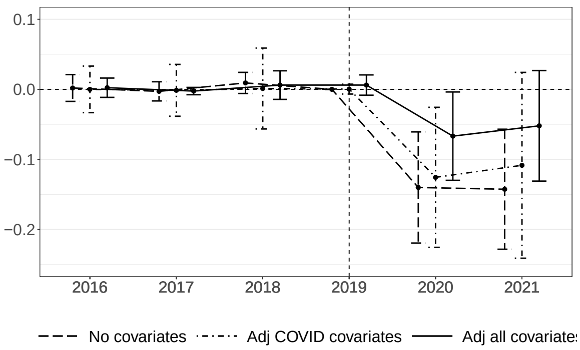
Note: Results are re-estimated by back dating the policy to 2019, prior to the actual policy implementation.

Figure D.2: ATTs and event study estimates - restricted sample

(a) ATTs since treatment in 2020 using the restricted sample

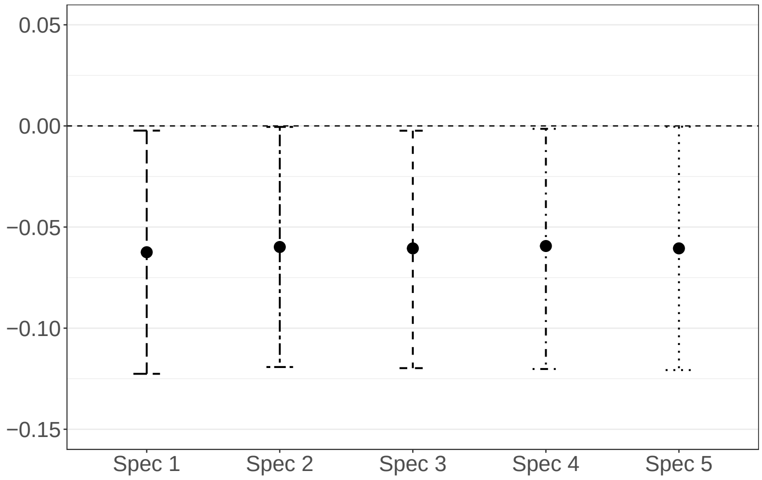


(b) Event study estimates for 2016-2021 using the restricted sample



Note: ATTs and event study estimates of the estimated impact of free public transport on road emissions (CO_2) per capita in Luxembourg using the restricted sample for different model specifications with 95% confidence bands based on placebo estimates.

Figure D.3: ATTs across different model specifications



Note: 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)	-0.0281***	-0.0265***	-0.0261***	-0.0307***	-0.0303***
	(0.00489)	(0.00480)	(0.00480)	(0.00515)	(0.00518)
asinh(nvrwfh)	0.0800**	0.102***	0.103***		
	(0.0265)	(0.0285)	(0.0286)		
asinh(wfh)	-0.0151*			-0.0224***	-0.0227***
	(0.00620)			(0.00525)	(0.00524)
log(gdp)	0.364***	0.384***	0.388***	0.343***	0.345***
	(0.0737)	(0.0752)	(0.0759)	(0.0756)	(0.0763)
log(ei)	0.226***	0.220***	0.224***	0.231***	0.236***
	(0.0423)	(0.0412)	(0.0418)	(0.0430)	(0.0435)
diesel	-0.756***	-0.770***	-0.782***	-0.767***	-0.779***
	(0.0885)	(0.0933)	(0.0898)	(0.0895)	(0.0863)
super	0.288*	0.274*	0.286*	0.284*	0.297**
	(0.111)	(0.114)	(0.112)	(0.112)	(0.109)
log(frt)		0.0158		0.0165	
		(0.00979)		(0.00945)	
Obs	816	816	816	816	816
N	136	136	136	136	136
T	6	6	6	6	6

Note: Size Standard errors in parentheses. Dependent variable is log(co2cap).
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

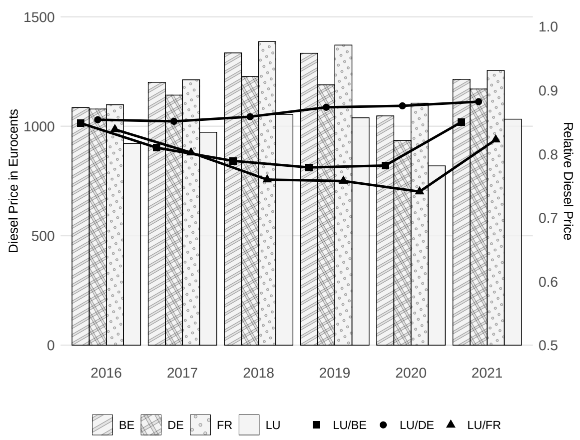
Table D.2: Pre- and post-treatment averages of relative fuel prices for Luxembourg

	Diesel		Petrol	
	Pre-Avg	Post-Avg	Pre-Avg	Post-Avg
BE	0.8010	0.8186	0.8765	0.9065
DE	0.8575	0.8794	0.8448	0.8401
FR	0.7892	0.7844	0.8253	0.7965

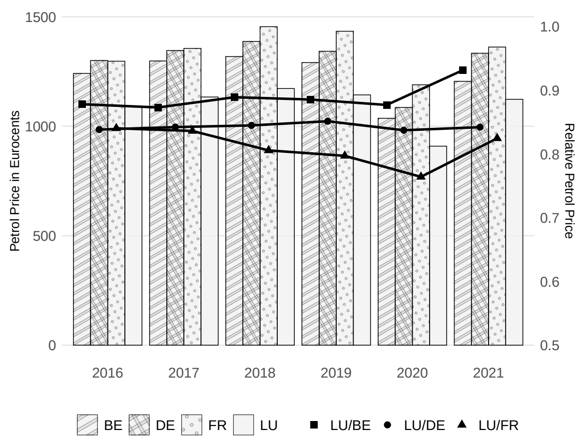
Note: Relative fuel prices of LU with respect to its neighboring countries. Pre-Avg are relative fuel prices based on time-weighted pre-treatment fuel prices, where time weights are taken from the SDiD main specification. Post-Avg are relative fuel prices based on post-treatment fuel prices.

Figure D.4: Absolute and relative fuel prices for LU and neighbouring countries

(a) Diesel



(b) Petrol



Note: Bars show fuel prices in Eurocents per 1,000 litres adjusted for inflation (HICP). Lines indicate fuel prices of Luxembourg relative to its neighbouring countries over time.

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