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 led to a reduction in road transport carbon emissions. We use spatial data from the European Emission Database on Global Atmospheric Research to construct a panel of carbon emissions for NUTS2 regions in the EU from 2016 to 2021. Given Luxembourg's unique characteristics among these regions, Difference-in-Difference and canonical Synthetic-Control methods are inadequate for finding a suitable counterfactual for Luxembourg. Instead, we employ the recently proposed Synthetic Difference-in-Differences method, which combines the advantages of both of these methods to create a suitable synthetic Luxembourg. We estimate an average reduction in road transport emissions of 6.1% over the period 2020-2021 attributable to the policy. To ensure a causal interpretation, we consider Luxembourg's distinctive characteristics and account for the concurrent COVID-19 pandemic as well as other challenges to address potential threats to identification. In particular, we control for confounding factors such as changes in commuting and working-from-home patterns as well as low-emission engine technologies and fuel prices. Event study analyses and sensitivity checks support the robustness of our results.

Keywords: Transportation, Emissions, Public Transport, Synthetic DID

JEL Codes: C21, C33, Q54, R48

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 transport can encourage a shift from private motorized transport to more environmentally friendly public transport. Such shifts can help reduce emissions from the transport sector. However, literature on the effects of *free* public transport is still scarce. 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 the quasi-experimental setting created by this policy intervention to empirically quantify its effect 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 (SDID) method to construct a suitable counterfactual for Luxembourg against which to compare post-intervention outcomes (Arkhangelsky et al., 2021).

Identification in this setting may be threatened by variations in mobility patterns arising from sources other than the free transport policy. The COVID-19 pandemic, which coincided with the implementation of the free transport policy, is a likely candidate for 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. We show that Luxembourg's response to the pandemic was not drastically different from other EU regions in terms of mobility patterns. Further, we control for these patterns in our models to refine identification. Additionally, the impact of COVID-related travel restrictions is another potential confounder. Again, these pose a threat to identification if Luxembourg experienced vastly different restrictions compared to other EU regions. To control for such restrictions, we study and control for daily regional variations in COVID-19 cases.

A further complication to identification is that Luxembourg is unique among EU regions. It has the highest GDP per capita, the highest motorization rate, and the highest per-capita CO2 emissions from transport in the EU. These factors complicate the identification process as they make it difficult to find comparable regions to build a counterfactual scenario. To address this, we conduct our analysis at the Nomenclature for Territorial Units for Statistics (NUTS) 2 level, as Luxembourg itself constitutes a

NUTS2 region. This level of analysis provides a more appropriate comparison in terms of emission trajectories compared to entire countries. The uniqueness of Luxembourg also complicates the parallel trend assumption required for a canonical difference-in-differences (DID) estimation. 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 depend on a donor pool of units similar to the treated unit conditional on the predictors of the outcome, 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. 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.

Our potential donor pool for constructing Luxembourg's counterfactual comprises of all other European countries at the NUTS2 regional 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 NUTS2 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 (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 the parallel trend assumption in the pre-treatment period. Additionally, we test the sensitivity of our results to various model specifications and apply a placebo test by backdating the policy's introduction to the year 2019. Our findings remain robust across these tests.

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 modeling approach and show that, while the policy significantly contributed to a modal shift from private vehicles to public transport, it did not significantly impact congestion levels. Our findings contribute to this narrative by providing an ex-post evaluation of the policy's impact on CO2 emissions. Other studies that look at the effect of free public transport are sparse. Tallin (Estonia) introduced free public transit in 2013. 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). 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 evaluate the impact on car usage or 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 (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. Li et al. (2019), for example, assesses the effect of subway expansion on air quality in China, while Lalive et al. (2018) investigates the impact of increased regional rail service in Germany. Additionally, Chen and Whalley (2012) explores 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 on the effects of fare reductions include, for instance, Aydin and Kürschner Rauck (2023) and Gohl and Schrauth (2024), which 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.

The rest of the paper is organized as follows. Section 2 briefly introduces Luxembourg's free public transport policy. Data and the identification strategy are discussed in Section 3. 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

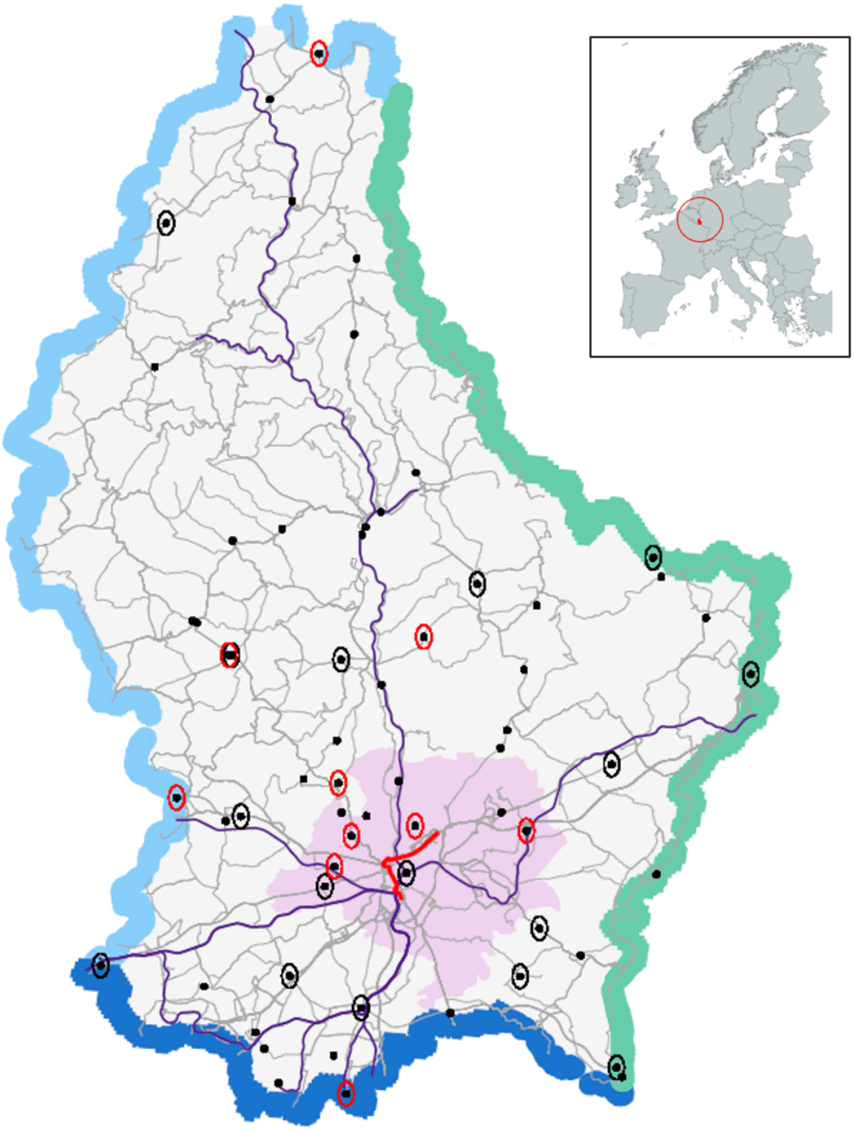
Luxembourg is different from other European countries in many ways. It is a small country in Western Europe and spans an area of about 2,586 km^2, making it one of the smallest countries in the EU. In the NUTS statistical region, it is a single region at all levels. The country hosts several EU institutions and its economic output mainly comes from banking and finance. Even though the country is one of the smallest in the EU both in terms of size and population, its GDP per capita at around 140,000 USD is the highest among all EU countries. The economic hub of Luxembourg is concentrated in its capital, Luxembourg City, which is located in the south of the country. The country experiences a large inflow of commuters from its bordering countries, Belgium, Germany, and France. Around 200,000 persons commute to Luxembourg on a daily basis, making up a relatively large share of its population of around 660,000. CO2 emissions from transport per capita are the highest among all EU member states at around 8,200 kg. Luxembourg also has the highest car density within the EU at around 700 cars per 1,000 inhabitants.

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). With the highest car density in Europe and facing significant congestion problems, Luxembourg designed this policy with the aim of reducing car usage. 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.

The existing public transportation infrastructure forms the backbone of this 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, offering quite a 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). 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).

The city of 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). Before the implementation of the free public transportation policy, Luxembourg charged differentiated public transport fares based on the duration and length of travel.

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 network. 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).

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.[1]

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, adding 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 can not 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, 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). 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 show those points for which we obtain an uninterrupted time-series over the period 2018-2022. The traffic posts circled have all experienced a decrease in annual bi-directional car traffic volume compared to 2019, and the ten bolded 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 will relate changes in traffic volume to our results more thoroughly in Section 7.

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

3 Data

We utilize the following data to estimate Luxembourg's free public transport policy effect. Spatial road transport CO2 emissions are extracted from the European Emission Database for Global Atmospheric Research (EDGAR) v8 (Crippa et al., 2022). Population data to convert emissions into per-capita terms is obtained from Eurostat's (2024) regional statistics. Covariates include the spatial distribution of daily COVID cases, obtained from Naqvi (2021). We use working from home and commuting inflow to control for mobility changes due to the pandemic. This data is obtained from a special extraction from the EU Labor Force Survey (EU-LFS). Fuel prices are taken from the European Commission's (2024) weekly oil bulletin and energy intensity of vehicles is available at EEA (2024). They are used to control for fuel price effects and adoption of low-carbon engine technologies, respectively. Data on loaded goods are again obtained from Eurostat's (2024) regional statistics and can help remove the effect of freight transport emissions from the data. Finally, we use data on real GDP per capita from from the regional statistics to control for overall different economic developments. After dropping missing data, we are left with 136 regions over the sample period 2016-2021, giving a total of 816 region-year observations. We now discuss the data and its sources in more detail.

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 evolution of road transport CO2 emissions for Luxembourg over space and time in Figure 2.[2] 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 values. Panel (b) shows the spatial distribution of average road transport emissions over the period 2016-2019, which constitutes our pre-treatment period. High emissions are indicated in darkblue and lower emissions in lightblue. 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 emis-

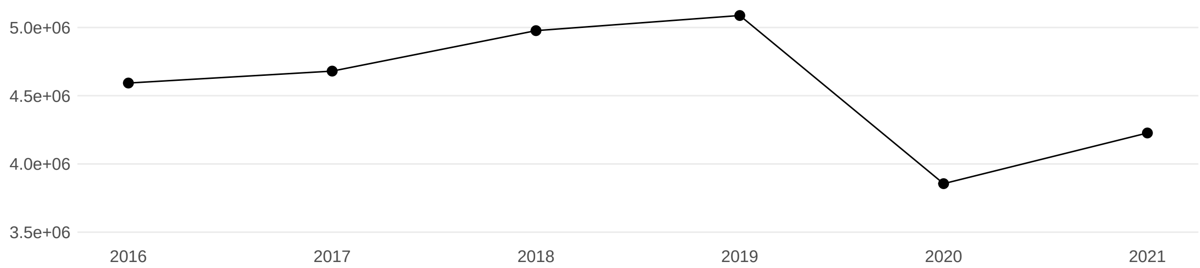
[2] Grid-cells that intersect with the NUTS 2 boundaries of Luxembourg are allocated according to their fraction that falls inside these boundaries.

sions. 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.

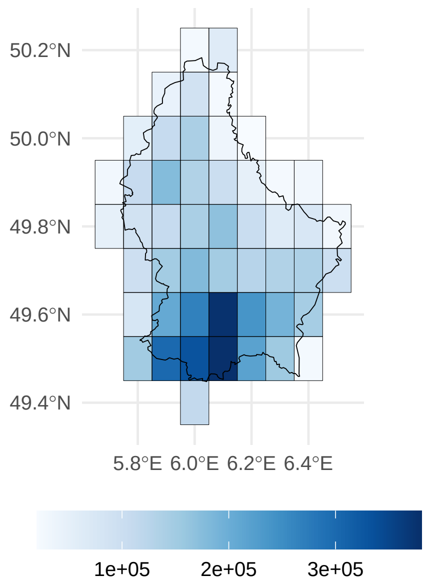
The reduction in CO2 emissions shown in Figure 2 is directly related to a reduction in fuel consumption, i.e., a shift in mobility patterns. This shift may be attributed to various factors. We are interested in the effect of free public transport, which is one potential source. Other likely source for the variation in CO2 emissions are COVID-related restrictions and reduced mobility as well as an increase in the number people working from home and fewer commuting trips.

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

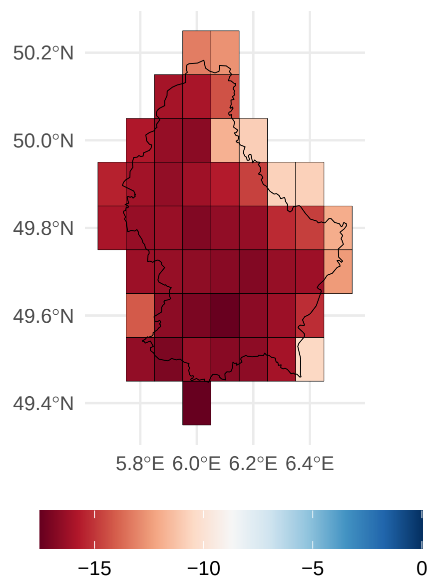
(a) Annual CO2 Emissions in Luxembourg



(b) Average Emissions 2016-2019



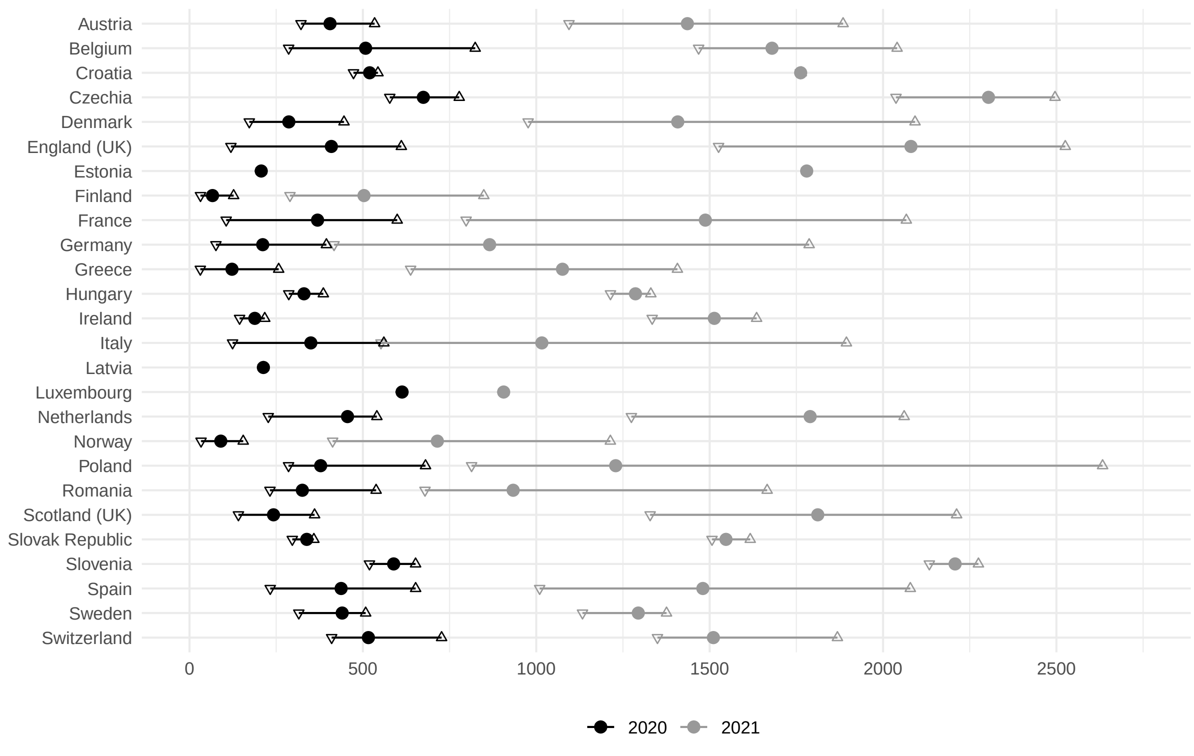
(c) %-Change 2020-2021 vs. 2016-2019



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.

Data on confirmed COVID-19 cases can indicate different policy responses and reduced mobility. This data is collected and reported by Naqvi (2021) up to the NUTS 3 level. Information on the number of confirmed cases is taken 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 (which is one reason why we do not extend our analysis to 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 3: Regional variation in COVID-19 cases for 2020 and 2021



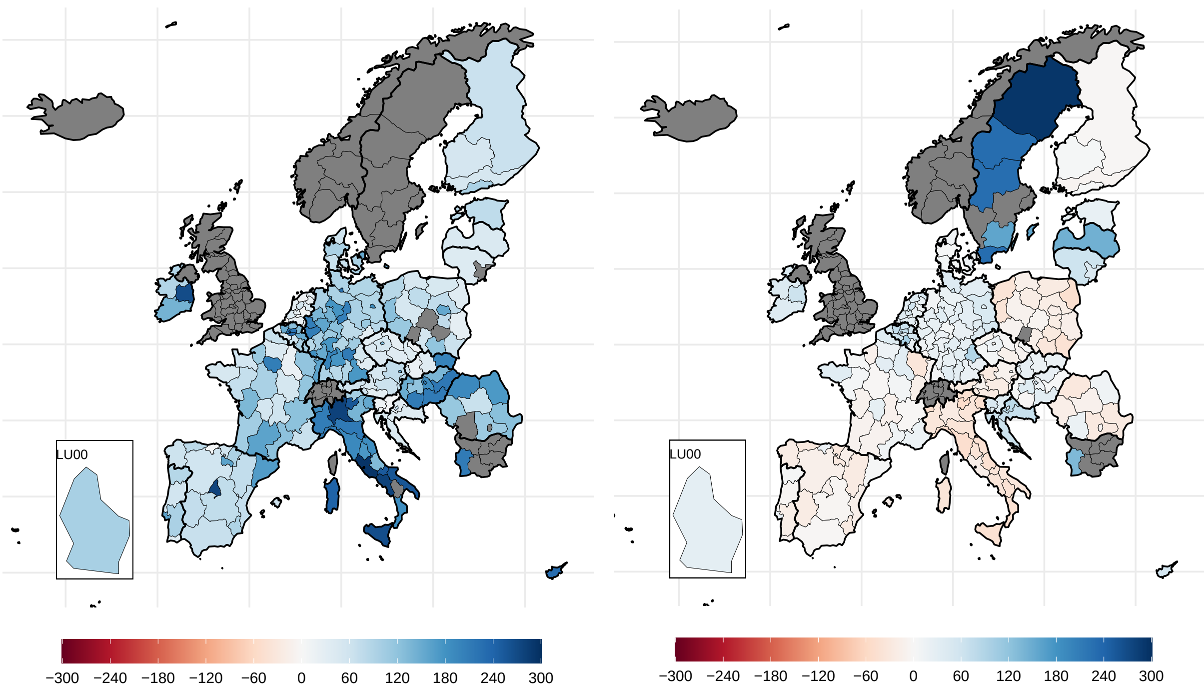
Note: Confirmed COVID-19 cases and their spatial distribution across countries for 2020 and 2021. Data for Luxembourg is from Our Wold in Data (OWID), while data for NUTS 2 regions in other countries is taken from Naqvi (2021).

Figure 3 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 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.

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.

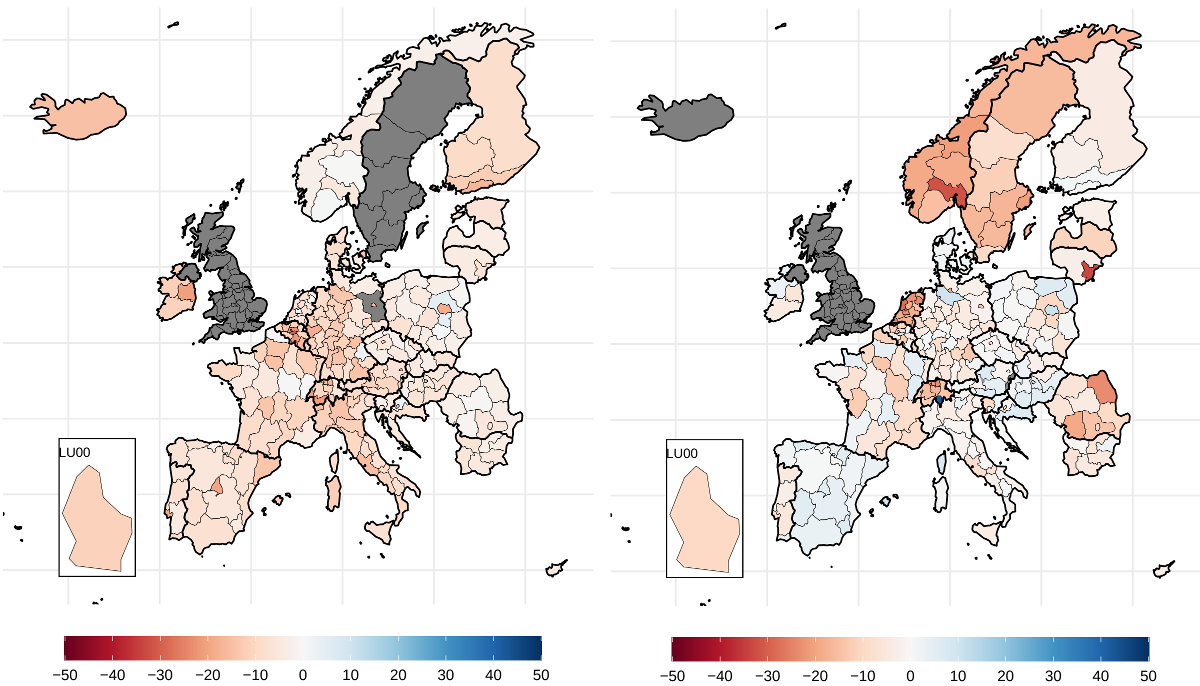
We use data on working from home and commuting inflow to further address changes in mobility behavior as a response to the pandemic. A person is classified as usually working from when they were working at home half of the days that they worked in a reference period of four weeks preceding the end of 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

[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.

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 5: 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 NUTS 2 regions which are the location of the workplace of these persons irrespective of their location of residence.

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 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. 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

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 had not been introduced?" To overcome this problem, it is necessary to design 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. 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 is motivated by the notion that some regions are more comparable to the treated unit than others. These procedures attach weights to units to create a synthetic control unit (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 NUTS 2 regional level to find more comparable control regions. This will be discussed in more detail in Section 5.

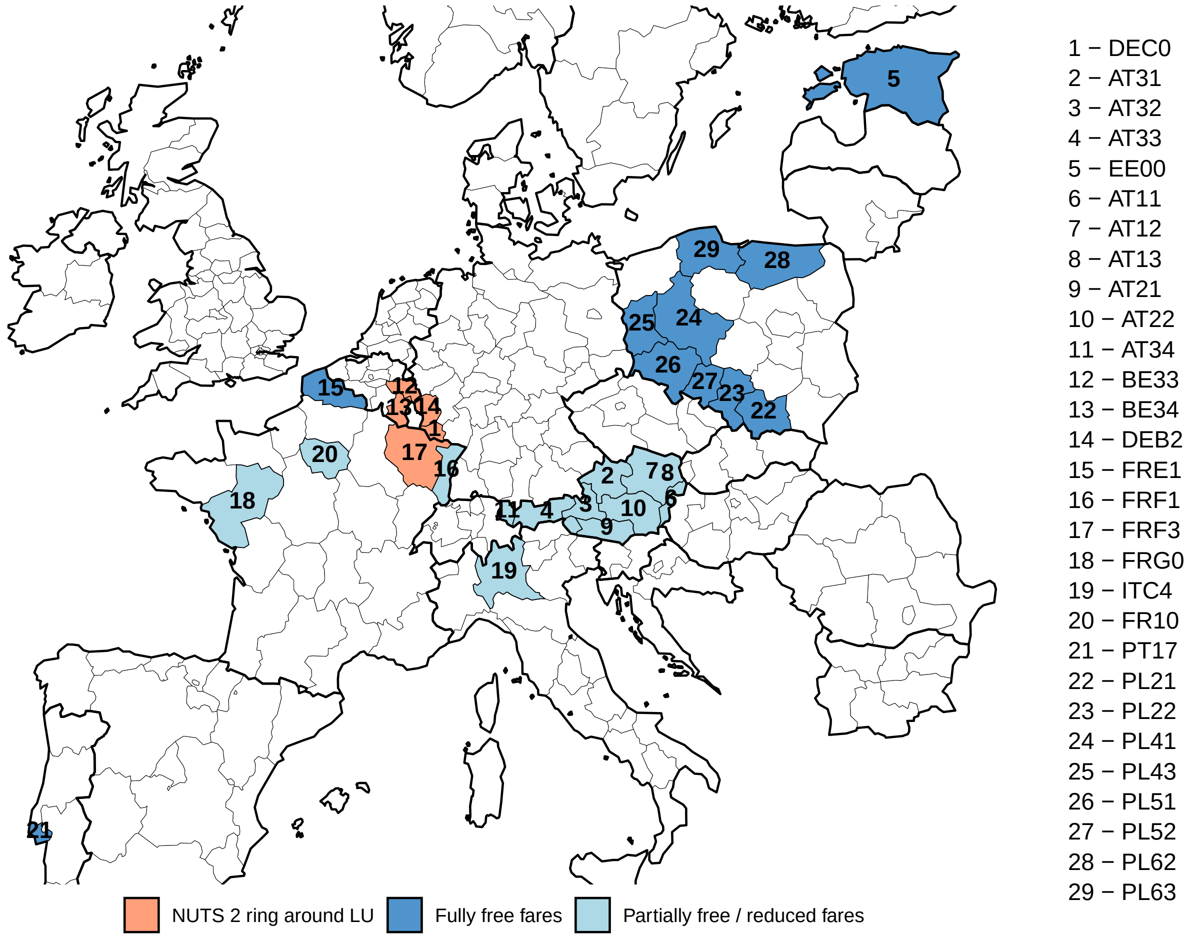
Identification is further threatened by variations in mobility patterns unrelated to the free-public-transport policy. The COVID-19 pandemic is a potential source of variation in mobility patterns unrelated to the free-public-transport policy in Luxembourg. A higher number of COVID-19 cases may, for 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 control for regional daily COVID-19 cases across countries. We have already seen in Figure 3 that COVID cases show a high variance across regions within countries. Luxembourg is at the high and low end of the distribution of cases among countries, but we can find more comparable units at the NUTS 2 regional level. This also emphasizes the necessity to conduct our study at a regional level rather than at the country level.

Another 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.

Both changes in working from home within a region (depicted in Figure 4) as well as in never working from home, i.e., commuting inflow (shown in Figure 5), 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 6.1 separately.

Finally, we want to avoid bad comparisons with already treated units. It is useful to distinguish between two types. First, units that implemented free fares during our sample period. Second, units that received such treatment before 2016. The former constitute bad controls and we drop NUTS 2 regions that include such cases. The latter type is not inherently problematic but will not provide additional information for our estimates either because their pre-treatment trend cannot be compared meaningfully to Luxembourg. As a consequence, such units are often dropped in related analyses. However, in our case, such units are mostly cities within NUTS 2 regions. This means that only a small part of the information contained within regions does not provide additional information. We therefore include regions that contain cities that introduced free fares prior to the start of our sample period.

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.

We drop the following regions to obtain our main results. Estonia (EE) introduced free public transport in Tallin in 2013 and extended it since. 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 that 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 NUTS2 regions in Europe to highlight those that are 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 in our robustness checks. The NUTS 2 ring around Luxembourg is shown in orange and is dropped in all specifications.

5 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.

5.1 Handling covariates

We 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 daily 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.

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 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). 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 (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, 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 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.

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-related variables as described in Section 5.1. The auxiliary regression is given by:

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

where the outcome variable is log of road-transport CO2 emission per capita. It is regressed on the inverse hyperbolic sine ($asinh$) of Covid $cases$, 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. Recall that the former covers people with their location of residency in the same country, while the latter is measured regardless of it. 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.[4]

[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 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: log of real gdp per capita, gdp, and energy intensity, ei, measured as average CO2 emissions of newly registered vehicles. Energy intensity captures the potential effect of emission reductions due to dissemination of more efficient vehicles, such as electric cars. This could bias our results if Luxembourg introduced more (or less) efficient vehicles relative to the synthetic control. Similarly, we include diesel and petrol prices in real terms (adjusted with the harmonized index of consumer prices - HICP) to capture cross-unit variations in fuel prices. In particular, we want to control for effects of national fuel-tax policies. Finally, we add log of freight transport, measured as tonnes of goods loaded in the region, to control for changes in freight transport. This allows us to interpret our estimates in terms of changes in passenger road transport emissions. 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 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 Covid-related effects - 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. This is encouraging and shows that the expansion in 2017 does not seem to have had a significant impact.

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 cases, 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. 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.

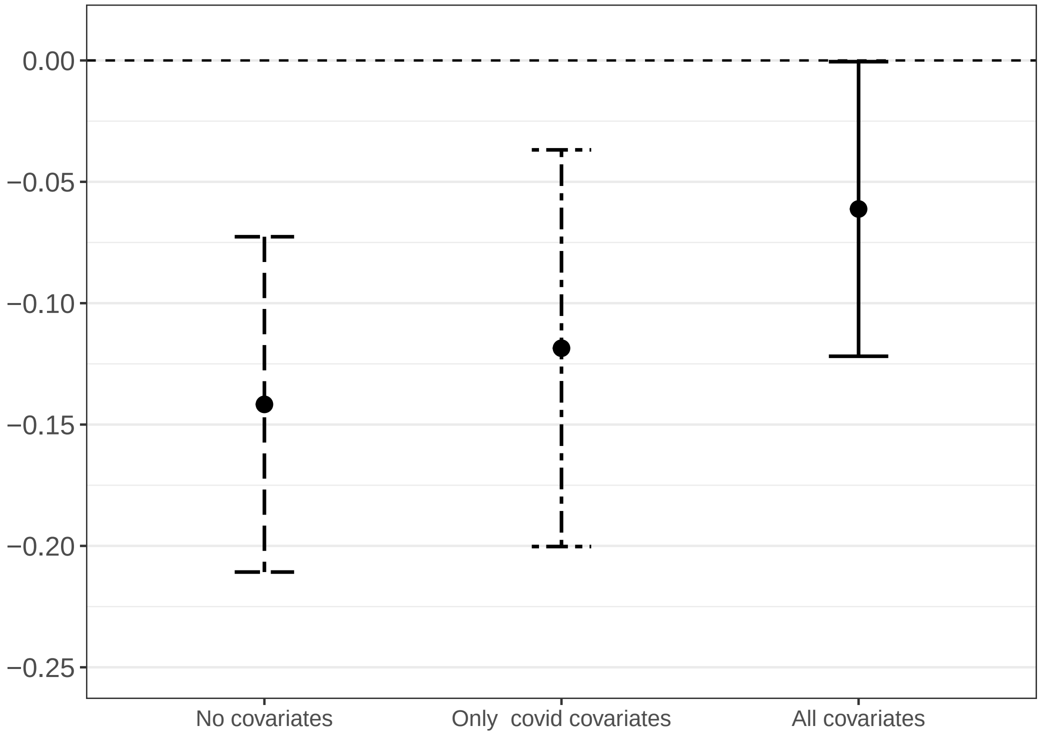
The control units that contribute to the synthetic control together with their respective weights for the third specification are graphically shown in Figure C.1 in Appendix C. The regions with the largest weights come from Belgium, Denmark, Spain, Hungary, Italy, and Poland. Regions from the Netherlands 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 gives 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. 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 how well the SDID-procedure 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 C.2a shows the absolute level of trends, while Figure C.2b standardizes the trends so that they are visually more easily comparable. 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 normalized 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 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 NUTS 2 regions.

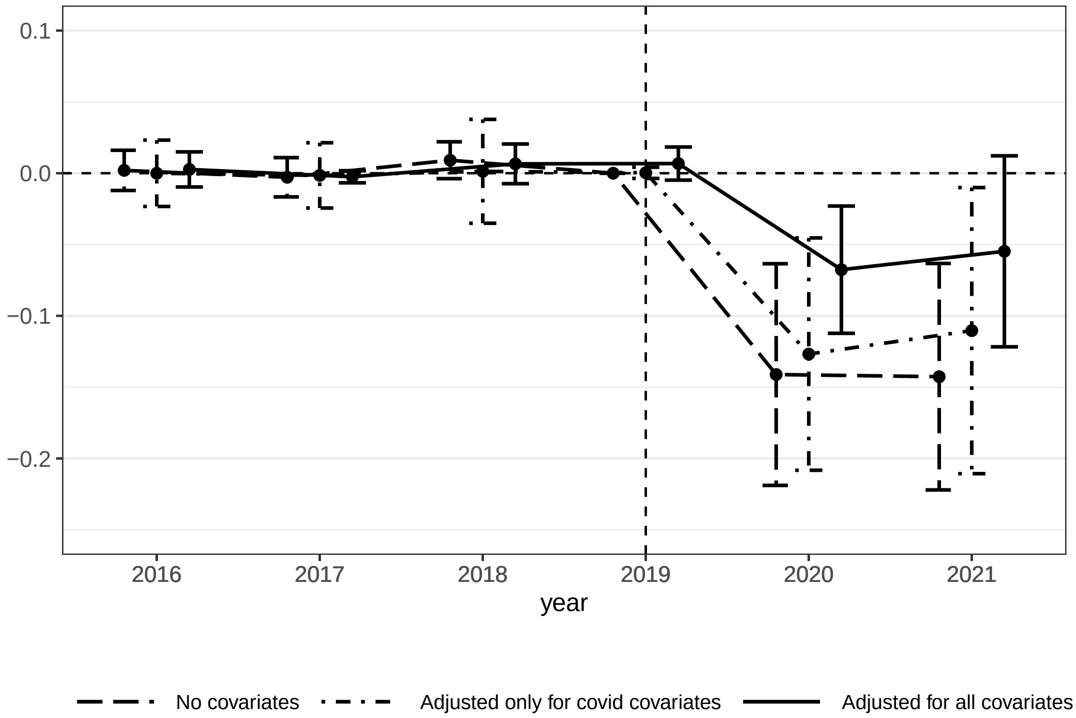
Regarding the evolution of *post*-treatment variables, we noted earlier that while Luxembourg experienced a decrease in commuters in the years after the pandemic, the mag-

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.

nitude 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.

6.2 Robustness

In this sub-section, we run a set of robustness tests to assess the sensitivity of our main results which are detailed below.

We have so far studied the three specifications shown in Figure 7, where the main specification includes all covariates. To further assess the robustness of our main results, 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[5], 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.1 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 regardless of the inclusion or exclusion of various controls.

Next, 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

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

E.1 in Appendix E shows the results of this test. 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 this post-placebo treatment effect provides further validation for our estimated results.

Finally, we 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. Specifically, we additionally exclude Torrevieja in Spain, Livigno 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 F.1 in Appendix F. 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 associated event-studies. Again, the trajectories and confidence bands are visually indistinguishable from the ones based on the larger sample.

Overall, the robustness checks confirm the stability and reliability of our main findings. The sensitivity analyses across different model specifications, the in-time placebo test, and the analysis using a restricted donor sample all yield consistent results, strengthening the validity of our conclusions. These tests provide strong evidence that our estimated effects are not driven by model specification choices or sample selection biases, lending credibility to our estimation results.

7 Discussion

In this section, we discuss the estimated effect size of Luxembourg's free public transport policy that was implemented in 2020 on CO2 emissions from road transport. We argue that the estimated ATT of around -6.1% is attributable to a modal shift from private motorised transport to public transport. We now want to discuss whether our estimated effect size is reasonable. Some might perceive 6.1% a small effect given the scope of the policy. Others might argue that this effect would be unreasonably large given a modal split in Luxembourg between public transport and private vehicles of around 80-15 (we will return to this issue in more detail below). We thus want to evaluate our estimate through some back-of-the-envelope calculations. This can be done from two perspectives.

One is by looking at changes in car traffic, and the other is 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 shows the total bi-directional car traffic volume across all the traffic posts. This volume increwased by around 7% in 2019 relative to 2018. Let us assume that in a scenario absent any interventions, this trend continues in subsequent years. Luxembourg's free transit policy was intended to counteract this trend and we estimate the policy effect at -6.1%. Under the assumption that the upward trend in car travel of around 7% would have persisted, the free transit policy should then reduce this trend significantly and almost negate it. Indeed, travel volume almost stagnated from 2019-2021 with a slight decrease of -0.4%. However, we cannot ignore COVID-19-related travel restrictions, which reduced mobility drastically in 2020. In Luxembourg, we observe a sharp drop in car travel of around 10% in 2020, which could be associated with the immediate impact of pandemic-related restrictions. The following year, 2021, saw an 11% rebound in car travel - an increase of almost identical magnitude as the drop in 2020. This might indicate a transient impact of the pandemic on car travel behavior. This thought-experiment at least suggest that the policy's estimated effect size is not implausible.

The traffic posts with bolded circles in Figure 1 represent the 10 posts with the largest decrease in bi-directional car traffic volume compared to 2019. Figure G.1 in Appendix G explicitly shows the annual bi-directional traffic volume for the years 2018 to 2021 for these top ten traffic posts. Examining the total annual traffic volume, we observe an upward trend in traffic counts up to the year 2019. As expected, there is a significant decline in 2020 across these posts, coinciding with the COVID-19 pandemic. However, the traffic counts for the years 2021 remain significantly lower than the pre-pandemic levels of 2019. This also indicates that the COVID-19 effect rather seems to have had a temporary effect in 2020, and that it did not structurally change the volume of traffic.

To further examine the compatibility of our estimates with observational data, we resort to changes in public transport usage of the tram, where usage data is available. Consider the following back-of-the-envelop calculations. 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. Our estimated reduction in CO2 emissions from road transport of 6.1% then leads to an estimated increase of public transport usage of around 33%.

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 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.

While the descriptive analysis does not validate the causal estimates directly, they do provide figures that are consistent with our estimated effect size.

8 Conclusion

We estimate the ATT of the free public transport policy introduced in Luxembourg in 2020 to be around -0.061, controlling for all covariates. This implies a reduction in CO2 emissions from road transport of around 6.1%. 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)	-0.0284***	-0.0119
	(0.0049)	(0.0072)
asinh(nvrwfh)	0.0789***	0.1217**
	(0.0264)	(0.0480)
asinh(wfh)	-0.0148**	-0.0459***
	(0.0062)	(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
T	6	6

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

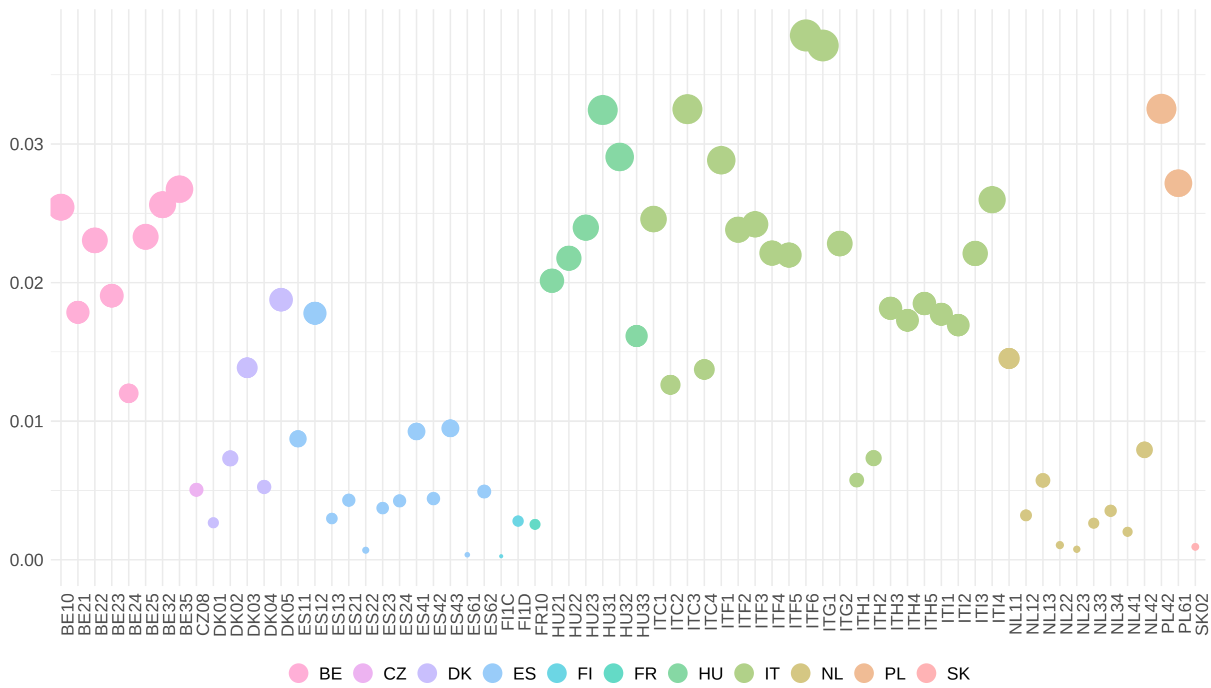


Table C.1: Summary values of selected variables in 2019 of NUTS 2 regions that received positive weights

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

Continued on next page

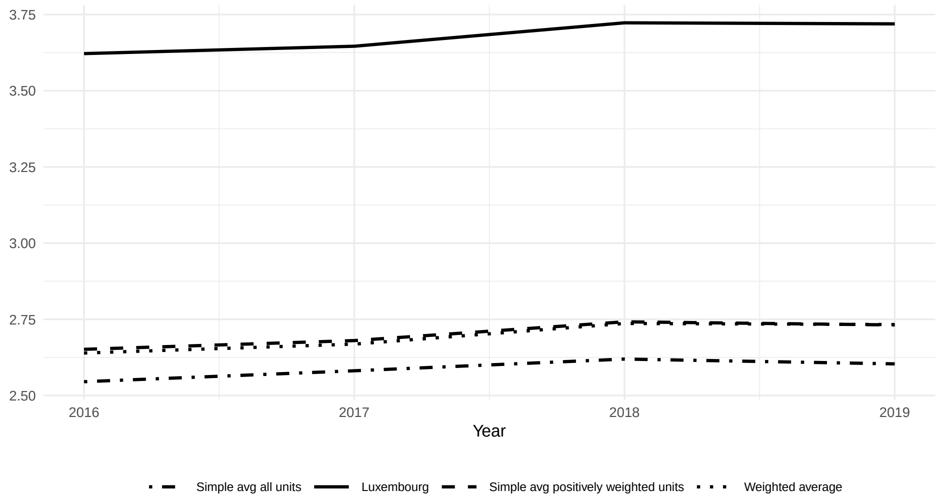
Table C.1 continued from previous page

NUTS2	Name	Weights	CO2pc	GDPpc	EI	NvrWFH	WFH	Diesel	Petrol
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
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

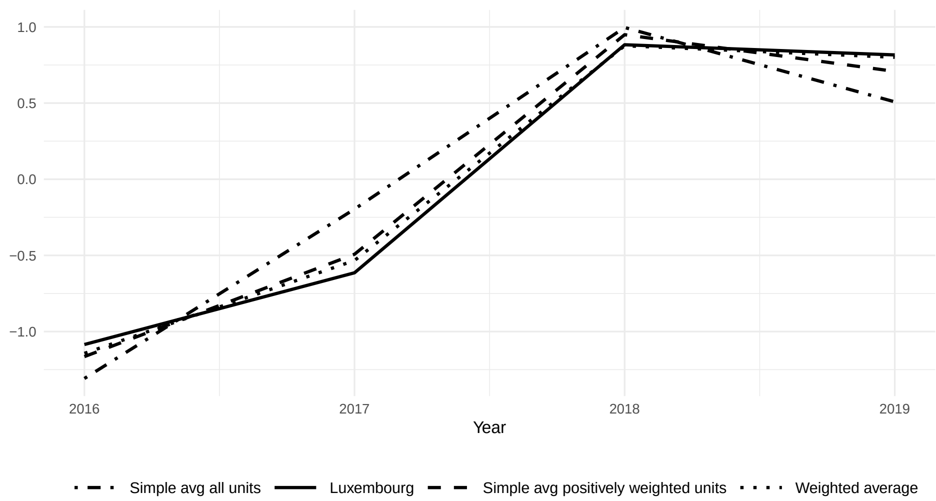
Note: *Weights* refer to unit weights assigned by the SDID method. *CO2 pc* is CO2 emissions measured in tonnes per capita. *GDP pc* is GDP per capita in Purchasing Power Standards. *EI* is the average CO2 emissions per km from new passenger cars. *NvrWFH* refers to all persons never working from home 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

(a) Absolute level



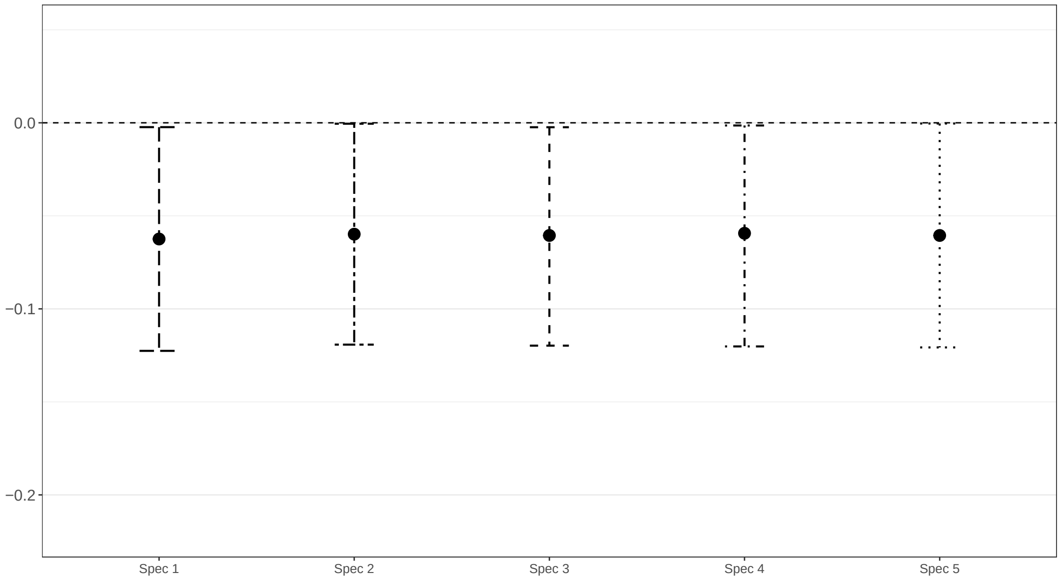
(b) Normalized outcome



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 a positive weights.

Appendix D

Figure D.1: 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.

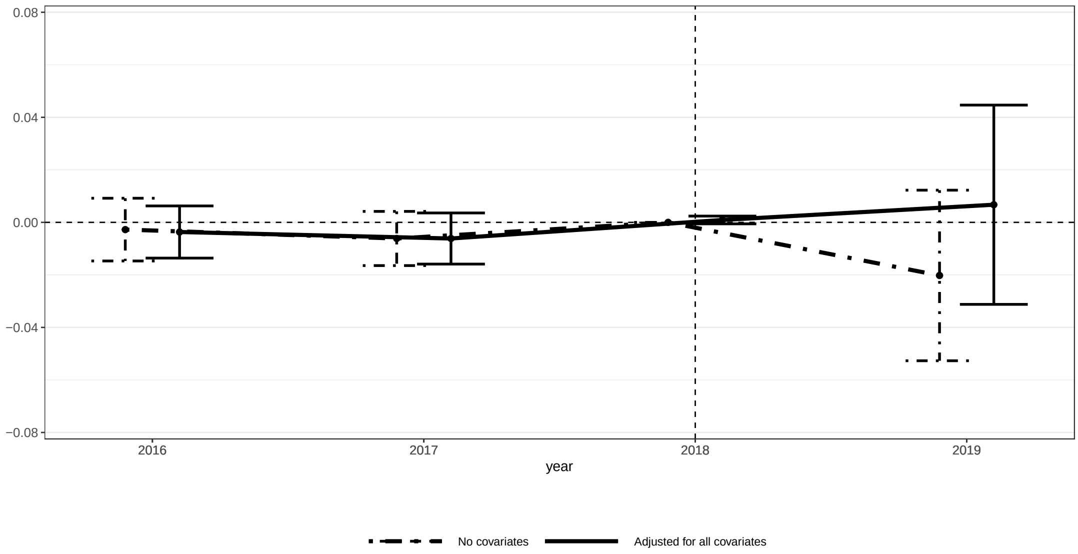
Table D.1: Sensitivity analysis across different model specifications

	(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). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix E

Figure E.1: In-time placebo test

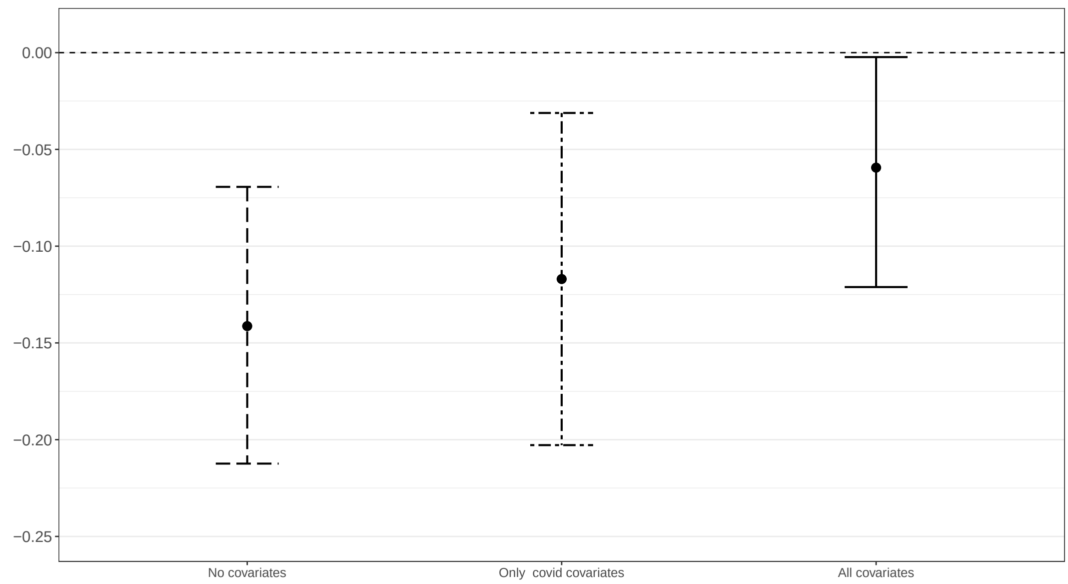


Note: Results are re-estimated by back dating the policy to 2019, prior to the actual policy implementation.

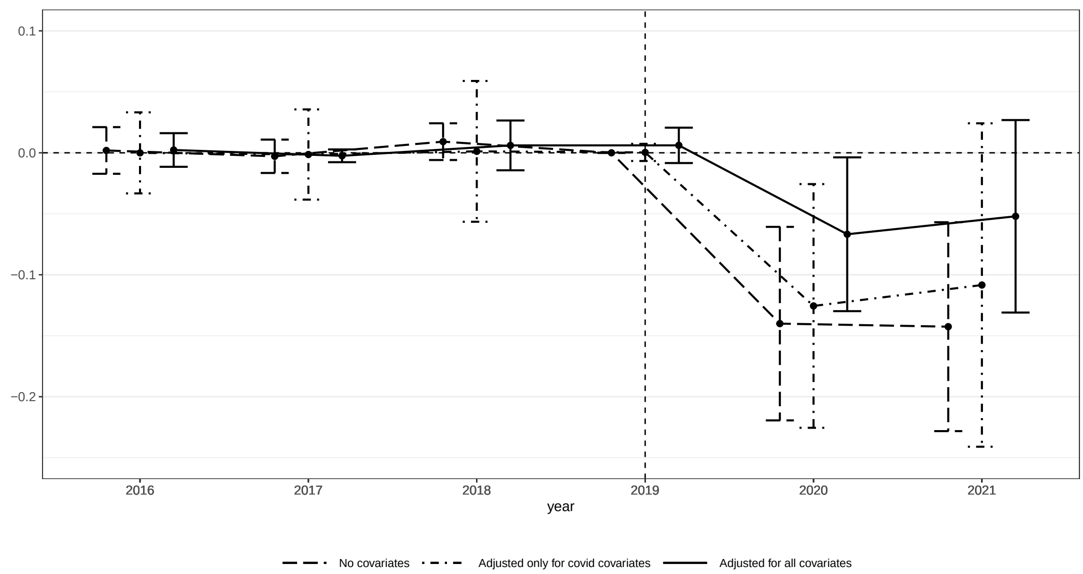
Appendix F

Figure F.1: ATTs and event study estimates - restricted sample

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



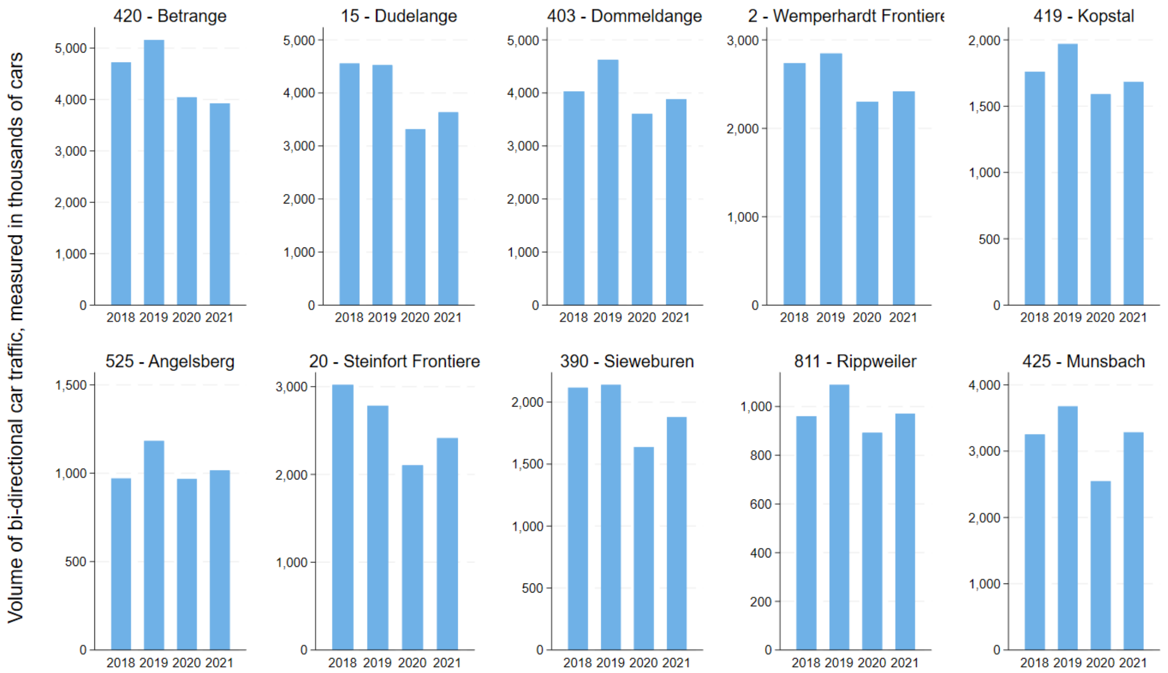
(b) Event study estimates for 2016-2021 using the restricted sample



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

Appendix G

Figure G.1: Volume of bi-directional car traffic



Note: 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 to the map of Luxembourg in Figure 1 for the corresponding location of the traffic posts.