# 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 emissions data to construct a panel of NUTS 2 control regions in the EU from 2016 to 2021. Our estimates indicate an average reduction of around 8% in road transport $CO_2$ 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

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). The provision of affordable and efficient public transport is often discussed as an effective way of reducing carbon ($CO_2$) 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.

We leverage this quasi-experimental setting in Luxembourg to causally identify and quantify the impact on $CO_2$ emissions in the road transport sector. To evaluate the effect of this policy, we use the recently introduced synthetic difference-in-differences (SDID) method to construct a credible counterfactual for Luxembourg and compare the post-intervention outcomes against it (Arkhangelsky et al., 2021). This allows us to isolate the policy's effect from other confounding factors to achieve robust causal inference.

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 $CO_2$ emissions from transport. These unique characteristics pose challenges in finding comparable regions for constructing a counterfactual scenario. To overcome 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] While entire countries may not serve as suitable comparison units for Luxembourg, other NUTS 2 regions such as Brussels, Amsterdam, or Paris offer more appropriate benchmarks. This level of analysis ensures a more meaningful comparison of emission trajectories.

To enhance the robustness of our identification, we employ SDID, which combines elements of traditional difference-in-differences (DID) and synthetic control (SC) approaches while overcoming their limitations in our context. The uniqueness of Luxembourg's case makes it less plausible that the parallel trends assumption required for DID estimation will hold. SC methods require a donor pool of units similar in predictors of the outcome to the treated unit–a requirement that is unlikely to be met in our setting. In contrast, the SDID method, combines elements of both DID and SC and allows us to construct a counterfactual $CO_2$ emission trajectory for Luxembourg from a pool of donor regions without relying on matches in absolute levels at any stage of the procedure–which is essential to draw causal inferences about the policy's impact in our specific setting.

Moreover, we address potential confounding factors related to the COVID-19 outburst. The pandemic likely caused variations in mobility patterns that are unrelated to the free

[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.

public transportation policy. However, this only complicates identification insofar as mobility behavior in Luxembourg changed differently compared to the control regions. To examine this, we draw on data on working from home and commuting inflow for Luxembourg. We find that Luxembourg's mobility patterns in response to the pandemic were largely consistent with those observed in other EU regions. We account for these patterns in our models to enhance the accuracy of our identification strategy. To control for regional variation in pandemic response, we additionally control for daily regional COVID-19 cases in our estimations.

The 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 137 NUTS 2 regions and 822 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 -0.083, i.e., to a reduction in $CO_2$ emissions from the road transport sector by 8.3%.

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, iteratively leaving out regions and countries from the donor pool, 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. We also carry out an SDID analysis on the $CO_2$ from energy use in the building sector to detect if our effect is purely driven by the impact of the COVID-19 pandemic. Our findings remained consistent across all these tests. Reassuringly, our estimates closely align with survey-based assessments of Luxembourg's free transit policy. We additionally extend our estimates to 2022 and find an increasing effect, but are cautious in interpreting these findings due to data quality issues and confounding factors (further discussed in Section -7).

We contribute to the literature by providing the first causal assessment of a free public transport policy on $CO_2$ 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 $CO_2$ emissions.

The existing literature on the effects of *free* public transport on $CO_2$ emissions is still scarce, largely because such policies were relatively uncommon. 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.

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 driving restrictions (Davis, 2008, 2017; Gallego et al., 2013), low-emission zones (Sarmiento et al., 2023; Wolff, 2014), road pricing (Gibson & Carnovale, 2015), and tax-based instruments (Andersson, 2019; Pretis, 2022).

The second type of policies promotes a shift to public transport, mainly by subsidizing public transit systems or improving infrastructure. This body of literature is particularly relevant to our study, as we also investigate the effects of improved public transport, specifically through enhanced access. Despite the apparent overlap between free transit and subsidized transit programs, we maintain that it is useful to distinguish between the two. While one might consider free transit merely a specific type of subsidy, factors such as user perceptions, convenience, and behavioral responses can diverge markedly when no fare is charged. Consequently, a fare-free system might lead to ridership patterns that differ from those observed in more traditional, partially subsidized scenarios.

Recent research on subsidized transit demonstrates mixed evidence regarding environmental outcomes. For instance, Aydin and Kürschner Rauck (2023) and Gohl and Schrauth (2024) evaluate the impact of Germany's 9-Euro ticket, introduced in 2022, and both report a decrease in air pollution, particularly in regions with robust public transit networks. However, contrasting findings are presented by Liebensteiner et al. (2024), who observe that while the 9-Euro ticket led to a significant increase in train rides during leisure hours, it only marginally reduced car usage. Similarly, Albalate et al. (2024) find no significant effect on air quality from a four-month public transport subsidy in Spain.

Research on public transit infrastructure provides additional insights. Li et al. (2019), Lalive et al. (2018), and Chen and Whalley (2012) show that expanding subway and rail services in China, Germany, and Taipei, respectively, improves air quality. Gendron-Carrier et al. (2022) find no average effect from subway openings across 58 cities, but reductions in pollution in more polluted cities. Overall, these studies suggest public transit investments can improve air quality, though outcomes vary by local context.

Some studies indirectly measure the effects of public transport in the absence of explicit policy interventions, using transit strikes to assess substitution between public and private transport. For instance, Anderson (2014), Adler and van Ommeren (2016), and Bauernschuster et al. (2017) find significant increases in congestion following transit strikes in Los Angeles, Rotterdam, and Germany's five largest cities, respectively.

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).

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 Section 7 our robustness tests. The results and potential mechanisms are discussed in Section 8. Finally, Section 9 provides concluding remarks.

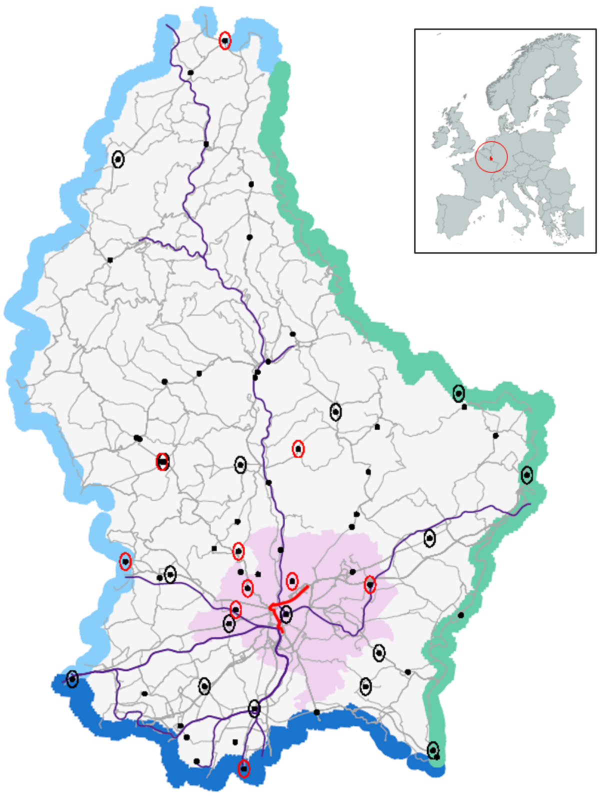
# 2 Background: Luxembourg and the policy

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 $CO_2$ 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 are in purple, 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: The map shows Luxembourg's borders with Belgium (light blue), Germany (green), and France (dark blue). Black dots indicate traffic posts, with circled ones showing a drop in traffic from 2019 to 2021; red-circled dots mark the top 10 largest declines. Light grey lines represent regional buses, dark purple lines are national rail, and the red line marks the tram. Luxembourg City is shaded in light pink. Public transport networks shown as of 2018; data is from Luxembourg's open data portal.

The city of Luxembourg is additionally served by the only tram line in the country, which covers around 10 km 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 most recent extension lies outside our sample period. Since the 2020 extension coincides exactly with the introduction of the free transit policy, it is impossible to disentangle their individual effects directly. However, we show in a robustness test that the 2017 expansion did not lead to significant reductions in emissions, suggesting that the comparatively minor 2020 extension is unlikely to have had a notable effect either. We will return to the latter aspect in more detail in Section 6.

Currently, the tram stretches over 10 kilometers, serves 17 stations, and includes 6 major interchanges (Département de la mobilité et des transports, 2024). Three more tramlines are planned to be completed by the end of 2035 (Luxtoday, 2022). Luxembourg also improved parking availability, particularly near border areas for its 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 traffic volume compared to 2019, and the ten red circles experienced the largest drop.

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

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 stagnated after 2019, on average.

# 3 Data

We combine the following data to estimate the causal effect of Luxembourg's free public transport policy on $CO_2$ emissions from road transport. Data on the outcome variable, per capita $CO_2$ emissions from the road transport sector, are constructed by combining spatial road transport $CO_2$ 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. We select emissions as our primary outcome variable not only because they directly relate to a core policy goal, but also because emissions data are consistently available as a panel dataset across regions. This availability is essential for conducting a robust causal evaluation in this context. In contrast, data on transit ridership or vehicle mileage remain scarce and are not always measured uniformly, making them less suitable for a systematic assessment of policy impacts.

To control for other factors that may influence $CO_2$ emissions from road transport, we include several covariates. Controls related to the pandemic include daily COVID-19 cases at the NUTS 2 level, sourced from Naqvi (2021), as well as data on working from home and commuting inflows, obtained from a special extraction from the EU Labor Force Survey (EU-LFS). Other controls encompass fuel prices, which we source from the European Commission's (2024) weekly oil bulletin. Energy intensity is taken from EEA (2024) and captures changes in efficiency of cars. Data on loaded goods is included to capture the effect of freight transport emissions and 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.

We drop regions with missing data and regions that experienced methodological breaks or data-quality disruptions in data generation to ensure a coherent balanced panel.[3] After additionally dropping bad controls (see Section 4), we are left with 19 EU countries (including Luxembourg) and a total of 138 regions over the sample period 2016-2021, giving a total of 828 region-year observations. The following subsections discuss in more detail the outcome variable, $CO_2$ emissions from road transport, and the COVID-19 related controls used in our analysis for this remaining set of countries.

[3] We drop the United Kingdom, Norway, Romania, Sweden, Switzerland, Liechtenstein, and Lithuania due to missing data. Germany experienced methodological and quality breaks in EU-LFS data generation.

## 3.1 $CO_2$ emissions data

Road transport emissions are categorized under the Intergovernmental 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 $\times$ 0.1 degrees. We aggregate these grid cells to the corresponding NUTS 2 regions for the following 19 located in Europe: Austria, Belgium, Croatia, Czech Republic, Denmark, Finland, France, Greece, Hungary, Ireland, Italy, Latvia, Luxembourg, Netherlands, Poland, Portugal, Slovakia, Slovenia, and Spain. The NUTS 2 regional borders are extracted from the Eurostat database (European Commission, 2022).

We present the evolution of $CO_2$ emissions from road transport for Luxembourg and other NUTS2 regions over time in Figure 2.[4] Panel (a) shows the evolution of the log of annual $CO_2$ emissions from road transport over the period 2016-2021. Luxembourg is indicated by the solid black line, while other NTUS 2 regions are shown in gray. The impact of COVID-19 can be seen in a drop in emissions from 2019 to 2020 across all regions. In 2021, an increase in emissions can be observed. However, both the drop and subsequent increase vary across regions.

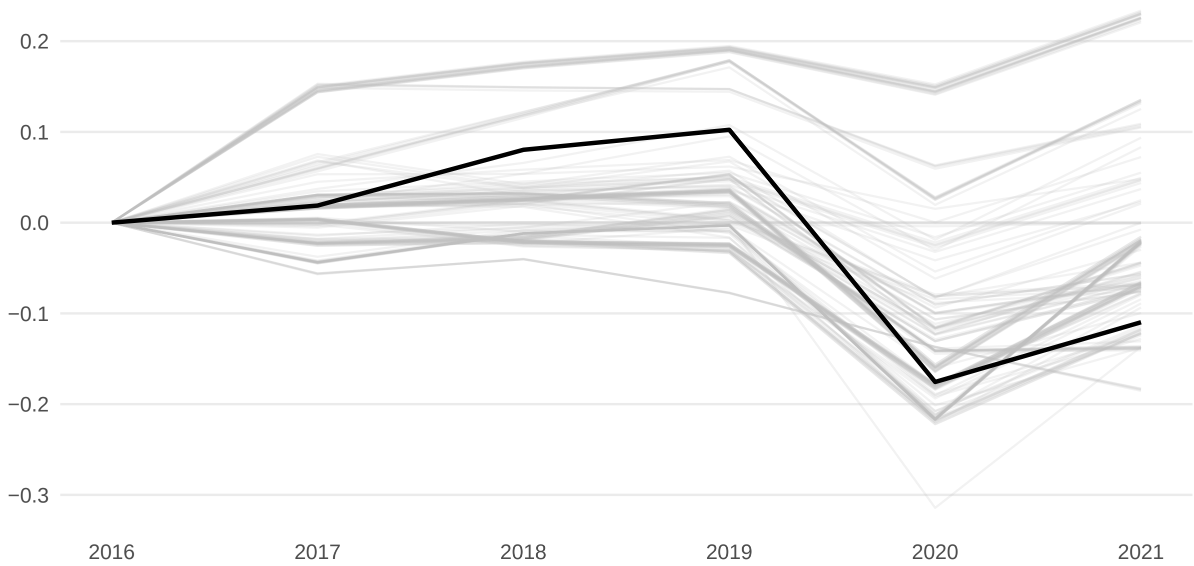
Luxembourg seems to have experienced a relatively large drop in 2020 relative to other regions, and emissions in 2021 stay consistently below pre-pandemic levels. Panel (b) shows the spatial distribution of average road transport emissions over the period 2016-2019, which constitutes our pre-treatment period. High emissions are indicated in 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 overall average emission reduction for the country for the post-treatment period relative to the pre-treatment period is around -17.5%. To extract the extent to which this reduction can be attributed to the free-public transport policy is the aim of our paper.

The reduction in $CO_2$ 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 $CO_2$ 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.

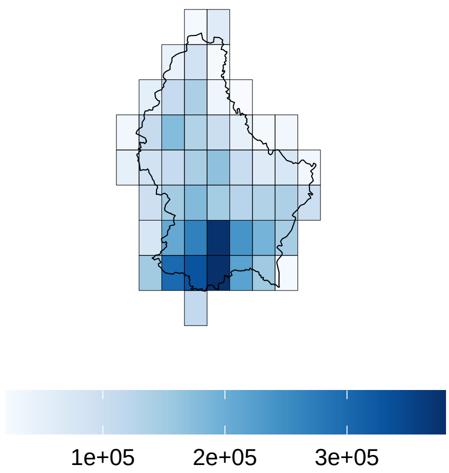
[4] Grid-cells that intersect with the NUTS 2 boundaries of Luxembourg are allocated according to their fraction that falls inside these boundaries.

**Figure 2:** Evolution of $CO_2$ emissions in Luxembourg over time and space

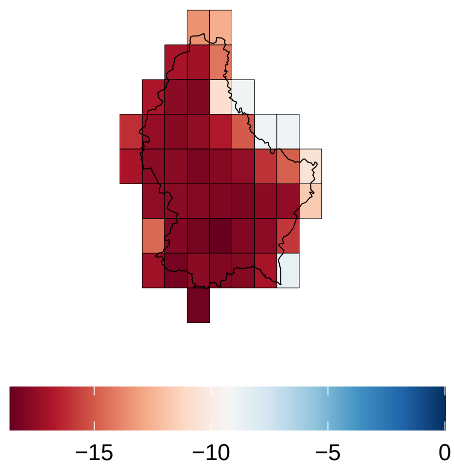
**(a)** Evolution of Log-$CO_2$ Emissions for Luxembourg and other NUTS 2 Regions




**(b)** Average Emissions 2016-2019




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




Note: Road transport $CO_2$ emissions (tons) are extracted from the EDGARv8.1 at 0.1x0.1 grid cells. (a) Shows the evolution of Log-$CO_2$ emissions, centered at zero in 2016. Luxembourg is indicated by the black line. (b) and (c) display spatial distributions of emissions for Luxembourg. (b) shows average emissions over the pre-treatment period, 2016-2019. (c) shows the %-change from average emissions over the post-treatment period (2020-2021) compared to the pre-treatment period.

## 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.

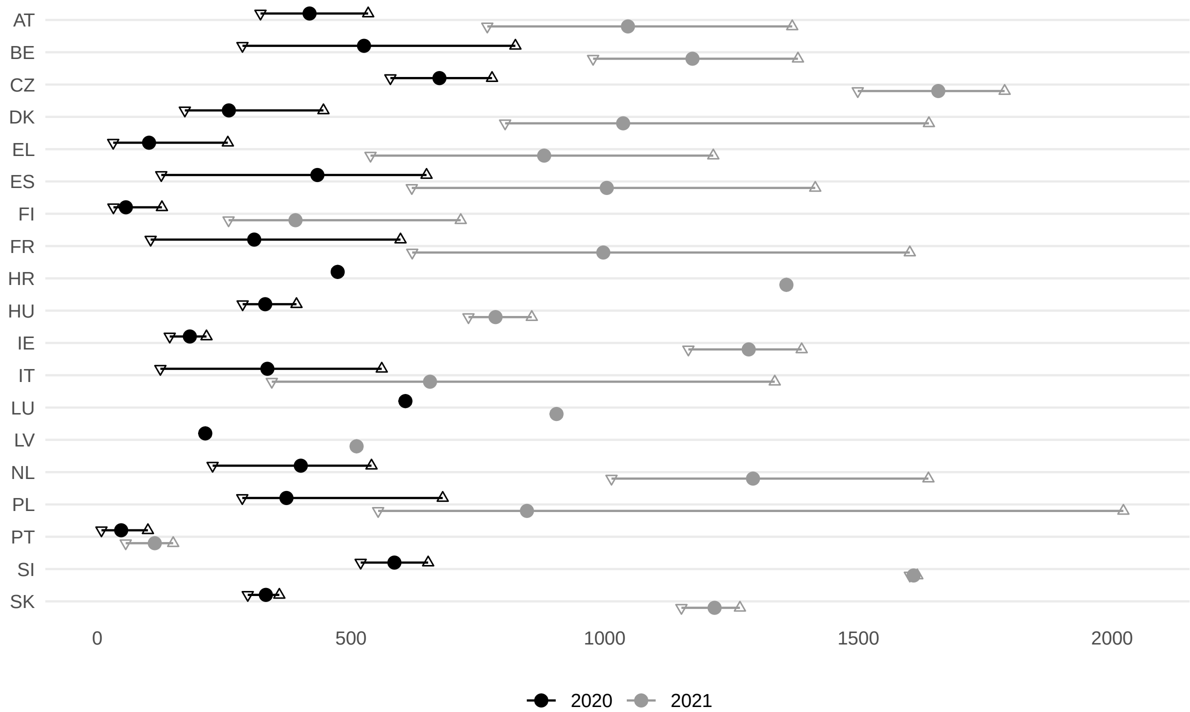
This data is collected and reported by the COVID-19 European Regional Tracker at the NUTS 3 level (Naqvi, 2021). Information on the number of confirmed cases is taken from each country's official institutions responsible for providing COVID-19 related data. The regional data is then aggregated up to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

**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).

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 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.[5]

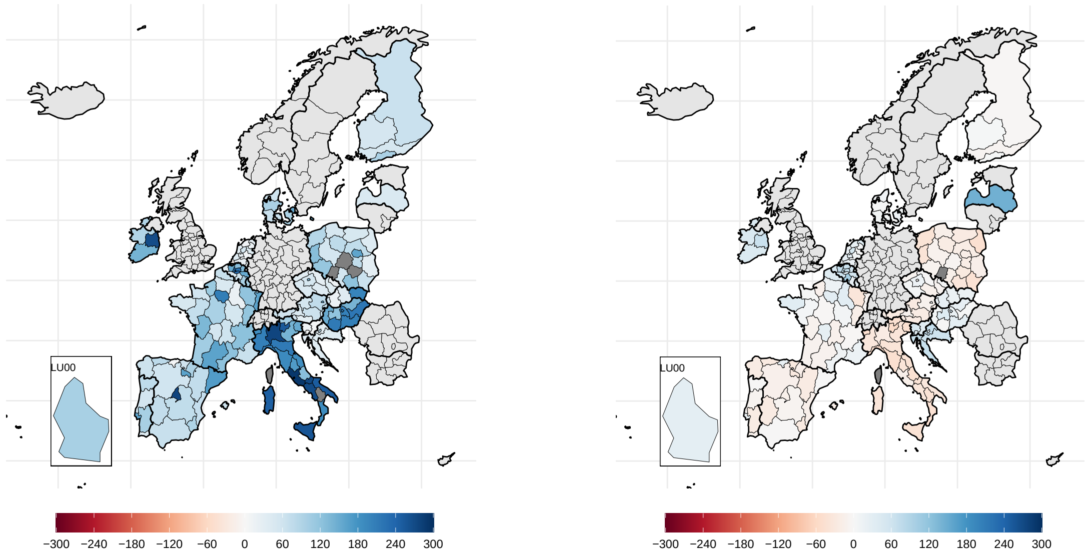
However, this dataset does not capture commuting patterns across regions, which seems particularly important for Luxembourg, which traditionally experiences a large commuting inflow. To get a more complete picture of changes in mobility behavior with respect to work, we consider persons never working 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

[5]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 4:** Change (%) in persons usually working from home for NUTS 2 regions

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

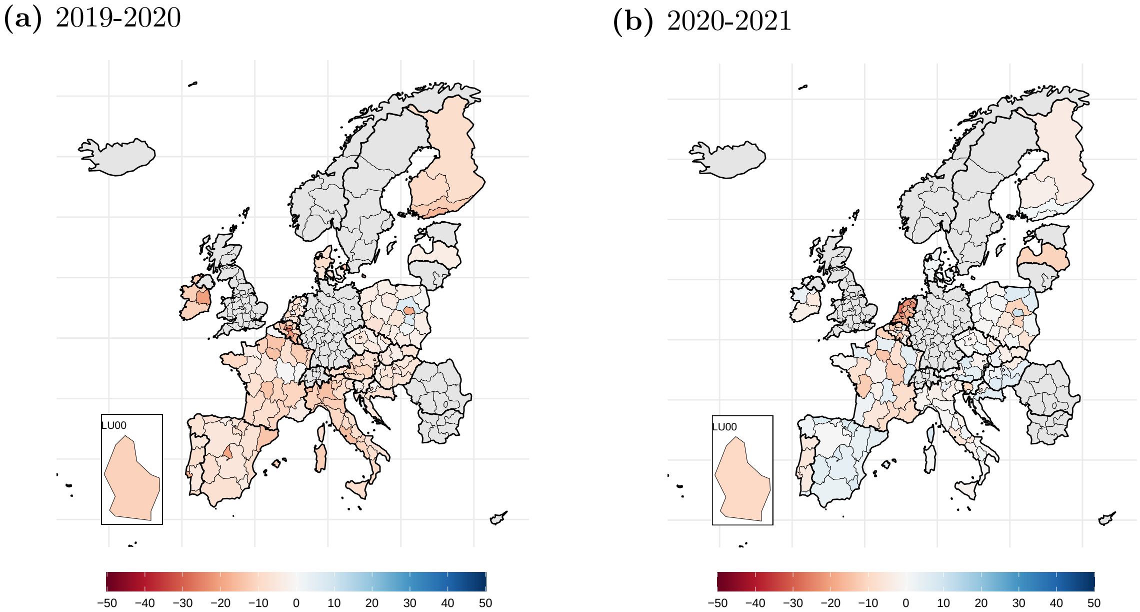



Note: Data is from a special extraction from the EU-LFS. Persons usually working from home with workplace at the NUTS 2 region shown in the figure and their location of residence in the associated country of the region.

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, 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.

**Figure 5:** Change (%) of persons never working from home for NUTS 2 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.

# 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 $CO_2$ 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 $CO_2$ 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. However, even at a NUTS 2 level, Luxembourg records the highest per capita $CO_2$ emissions from road transport. 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 $CO_2$ 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 $CO_2$ 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 for Luxembourg. Section 5 discusses the SDID estimation procedure in detail.

Identification is further complicated by the COVID-19 pandemic, which coincides 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 shifts 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.

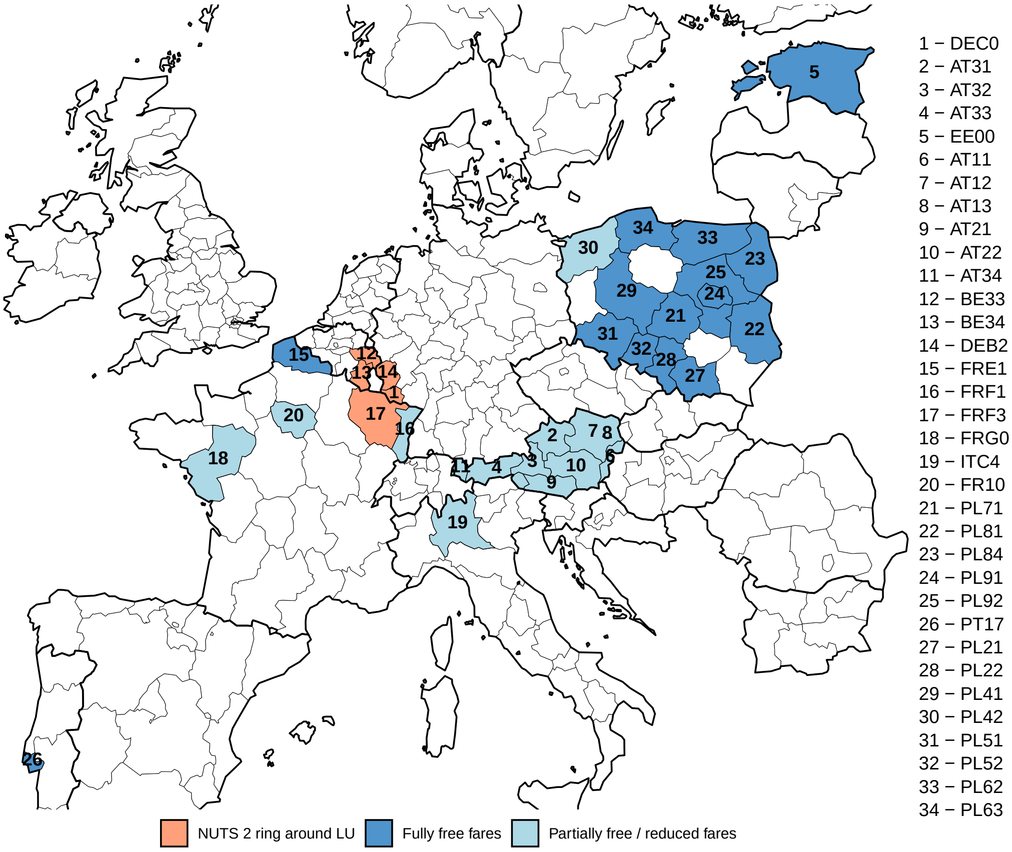
Finally, to avoid bad comparisons with already treated units, we excluded NUTS 2 regions that introduced free fares during our sample period. We drop the following regions before estimating our main results. Estonia (EE) introduced free public transport in Tallin in 2013 and further extended it in 2017. 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 (PL21, PL22, PL41, PL51, PL52, PL62, PL63, PL71, PL81, PL84, PL91, PL92). 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 ("City Public Transport Information," 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

**Figure 6:** NUTS 2 regions - bad controls




Note: NUTS 2 regions that are potential bad control are highlighted. A NUTS 2 ring around Luxembourg in orange, regions that introduced free fares during our sample period in dark blue and regions that introduced reduced fares or partially free public transport in light blue.

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.

# 5 Synthetic difference-in-differences (SDID)

We use the SDID methodology to estimate the impact of Luxembourg's free public transport policy on $CO_2$ 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. Schenk (2023) shows that the SDID estimator performs remarkably well in short $T$ panels, is able to handle interactive fixed-effects that can influence the outcome, and provides conservative standard errors. Considering the few pre- and post-treatment periods in our sample, this reassures us that the applied methodology is consistent under our setting.

The SDID estimator aims to consistently estimate an ATT without relying on parallel pre-treatment trends between treated and not-treated units. 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.

The SDID-ATT is estimated by:

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

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. $\mu$ is an intercept, $\alpha_i$ and $\beta_t$ 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:

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

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. $\zeta$ 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:

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

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.

## 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 $CO_2$ 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, $\alpha_i$, and time-specific effects, $\gamma_t$. 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 $CO_2$ 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:

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

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

# 6 Results

This section reports our main results as well as several robustness checks. We study several model specifications, which are outlined in Section 6. Section 7 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.

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:

$$\begin{aligned} log(CO_2/cap)_{it}^{co} = &\alpha_i + \gamma_t + \beta_1 asinh(cases)_{it}^{co} + \beta_2 asinh(nvrwfh)_{it}^{co} + \\ &\beta_3 asinh(wfh)_{it}^{co} + u_{it}, \end{aligned} \tag{7}$$

where the outcome variable is the log of road transport $CO_2$ 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.[6]

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

$$
\begin{aligned}
log(CO_2/cap)_{it}^{co} = & \alpha_i + \gamma_t + \beta_1 asinh(cases)_{it}^{co} + \beta_2 asinh(nvrwfh)_{it}^{co} + \\
& \beta_3 asinh(wfh)_{it}^{co} + \beta_4 log(gdp)_{it}^{co} + \beta_5 ei_{it}^{co} + \\
& \beta_6 diesel_{it}^{co} + \beta_7 petrol_{it}^{co} + \beta_8 log(frt)_{it}^{co} + u_{it}.
\end{aligned} \tag{8}
$$

The set of covariates that we consider in this specification additionally includes: the log of real GDP per capita, ($gdp$), energy intensity, ($ei$), measured as average $CO_2$ emissions of newly registered vehicles, ($diesel$) and ($petrol$) prices in real terms (adjusted with the harmonized index of consumer prices - HICP) to capture cross-unit variations in fuel prices, and the log of freight transport ($frt$), 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 (7) and (8) are shown in Table A.1 in Appendix A.

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 COVID-19 related covariates - adj COVID covariates, and 3) adjusting for the full set of covariates - adj all covariates. The latter specification produces our main results. The time weights for this variant are assigned to 2018 and 2019 with weights of 0.3348 and 0.6652, 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 $-0.083$, i.e., a 8.3% reduction in transport $CO_2$ 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.

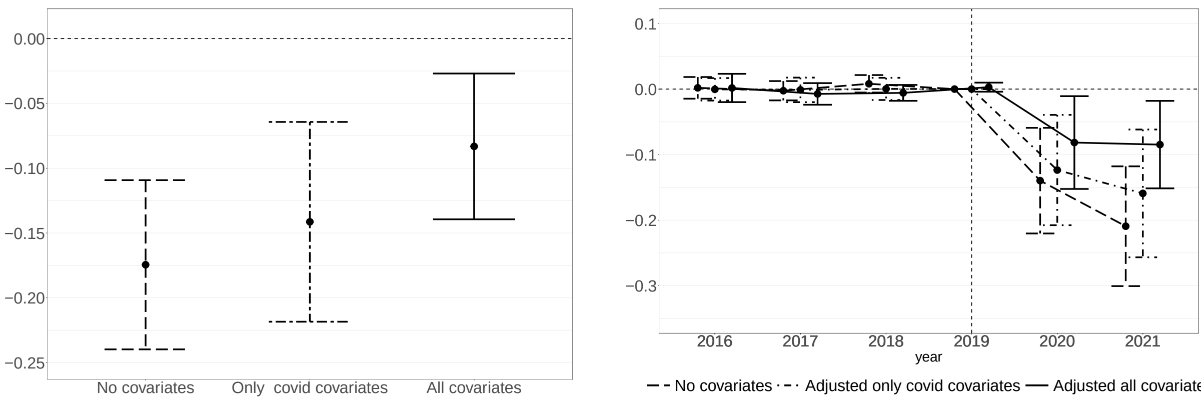
The event-study analysis shows no violation of parallel pre-treatment trends for all specifications. This also indicates that the tram extension in 2017 did not significantly alter Luxembourg's emissions trajectory compared to our synthetic control. Post-treatment effects show statistical significance in 2020 for all three specifications. In 2021, the confidence intervals based the specifications that adjusts the outcome variable for all covariates

[6] 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.

slightly cross the dashed zero-line at the 5% significance level.

**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 ($CO_2$) per capita in Luxembourg for different model specifications with 95% confidence bands based on placebo estimates.

The control units that contribute to the synthetic control together with their respective weights for the third specification are graphically shown in Figure B.1 in Appendix B. The regions with the largest weights come from Belgium, Denmark, Spain, Finland, Italy, Netherlands, and Portugal. In addition, Austria, Czechia, Greece, France, Hungary, Ireland, and Latvia receive weights. 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 Italy is among EU countries with the highest motorization rate after Luxembourg. It is therefore quite reasonable that the regions contributing to the synthetic control are taken from these countries.

Figure B.2 in Appendix B 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 SDID unit weights as a dashed line. The figure also shows 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 (a) shows the absolute level of trends, while Figure (b) standardizes the trends so that they are visually more easily comparable.[7]

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. 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

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

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.

# 7 Robustness

The credibility of the SDID estimator depends on its ability to reproduce a counterfactual outcome for Luxembourg in the absence of the free public transport policy. In this section, we conduct standard robustness tests commonly used for synthetic controls, an *in-time placebo test*, where the policy is backdated to a fictitious date, as well as *leave-one-out placebo tests* to assess the sensitivity of the synthetic control to the composition of the donor pool (Abadie, 2021). Additionally, we examine the robustness of our results to different model specifications. Finally, we apply the SDID method to $CO_2$ from energy use in the building sector to assess whether there was an effect attributable to COVID-19. Finally, we extend our post-treatment period by one year and discuss the results of this analysis.

**In-time placebo**: We perform an in-time placebo (also referred to as back-dating test) as suggested by Abadie (2021). Here, we assign the free public transport policy to 2019, the year before its actual introduction. Since the treatment is artificially assigned to a prior date we should not observe a significant post-placebo treatment effect. Figure C.1 in Appendix C shows these results. The solid black line represents our main specification with all covariates, and the dot-dash line represents the specification without covariates.[8] The confidence bands at the 5% significance level encompass the zero line, indicating no significant treatment effect in 2019.

**Leave-one-out placebo**: We use a donor pool of 137 NUTS 2 regions in our analysis. To assess the sensitivity of our results, we conduct a leave-one-out robustness check by iteratively excluding one region at a time, re-estimating the SDID model, and obtaining a distribution of ATT estimates. The resulting distribution is presented in Figure C.2a in Appendix C. The estimated ATTs from this exercise range from -0.085 to 0.081, with our main estimate of -0.083 positioned near the center of the distribution. These estimates are not statistically different from our main result, indicating that our findings are robust to the exclusion of individual regions from the donor pool.

Next, we extend this robustness check by iteratively excluding one country at a time. Since the 137 NUTS 2 regions in the donor pool in our sample span 18 countries, this approach removes multiple regions at once. The resulting ATT estimates, plotted in Figure C.2b in Appendix C, range from -0.0962 to -0.0793. The results exhibit greater sensitivity compared to the leave-one-NUTS 2 region at a time analysis, as dropping an entire country removes a substantial number of regions simultaneously. Nonetheless,

[8]We do not estimate the specification adjusted only for COVID-19 covariates since the policy is back-dated before the pandemic.

our main estimate of -0.083 remains centrally located within the distribution. The most pronounced deviations occur when we exclude Italy (-0.0962) and the Netherlands (-0.0902). Dropping Italy removes 21 NUTS 2 regions, while excluding the Netherlands removes 12 NUTS 2 regions. Notably, both Italian and Dutch regions receive high weights in our main specification (see Appendix B.1). The fact that our estimates shift in a direction that strengthens our main result suggests that, if anything, our primary findings are conservative.

**Restricted sample:** We also conduct our analysis on a more restricted donor sample by excluding regions that introduced any form of public transport subsidy affecting specific segments of the population, as described in Section 3. We further exlcude 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 ("City Public Transport Information," 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. These results are reported in Figure C.3 in Appendix C. 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 evaluate the robustness of our main results in Figure 7, we explored sensitivity across alternative model specifications. Given that our measures for people working from home and those commuting to work likely capture similar dynamics[9] to a certain degree, we test the sensitivity of our results by excluding one or the other from our specifications. Additionally, Table A.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 C.4 and Table C.1 in Appendix C. All five alternative specifications yield estimates similar to our main specification.

**Fuel tourism:** Luxembourg's lower fuel prices compared to neighbouring regions can attract fuel tourism, which can then lead to increased fuel consumption and higher 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

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

accounted for by fuel prices of Luxembourg relative to its neighbours. Figure C.5 in Appendix C compares both absolute and relative fuel prices between Luxembourg 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. 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. The estimated ATT is $-0.0839$ and is statistically indistinguishable from our main result ($-0.0832$). 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 C.2 in Appendix C, there is no significant difference between these weighted averages for diesel and petrol prices in Luxembourg relative to its neighbors.

**Energy for buildings**: While the pandemic undeniably led to temporary reductions in mobility and emissions globally, our SDID approach inherently accounts for this, as the donor pool is composed of NUTS 2 regions also affected by COVID-19. If COVID-19 were the primary driver of the observed emission reductions, we would expect similar declines in road emissions in synthetic Luxembourg as well, yet this is not what we find. Moreover, we conducted a placebo test using $CO_2$ from energy use in buildings, which should also have been affected by pandemic-related shifts in energy demand (e.g., increased residential electricity use due to lockdowns and remote work). If COVID-19 were driving a broad reduction/increase in emissions, we would expect to see an effect in this sector as well. However, we find a null effect, suggesting that the reduction in road $CO_2$ is not merely a byproduct of the pandemic. This strengthens the argument that the free public transport policy itself played a causal role in reducing $CO_2$ rather than reflecting a general COVID-19 induced effect. The results of this analysis is reported in Figure C.6 in Appendix C.

**Extending the post-treatment period to 2022**: We extend the post-treatment period by one year to 2022, with the results presented in Figure C.7 in Appendix C. When including this additional year, we observe a further reduction in road transport $CO_2$ emissions, leading to an increase in the estimated ATT for the post-treatment period. This result is expected, as Luxembourg's free public transport policy is an ongoing intervention rather than a short-term measure, allowing individuals to gradually adjust their travel behavior over time. However, we do not adopt this as our main specification for three reasons. First, the 2022 EDGAR data are still estimates and subject to revision. Second, COVID-19 case reporting in 2022 was inconsistent, with most regions ceasing to report cases after September, making it difficult to control for pandemic-related effects. Finally, Luxembourg made additional investments in public transport infrastructure in 2022. This makes it more challenging to isolate the effect of the free public transport policy from the broader improvements in public transit accessibility.

# 8 Discussion

We now discuss the estimated effect size of Luxembourg's free public transport policy. We attribute the estimated ATT of $-8.3\%$ to a modal shift from private motorized transport to public transport and ask whether this estimated effect size is reasonable.

Consider the following back-of-the-envelop calculation. Following figures from the European Commission and Directorate-General for Mobility and Transport (2021), we assume a modal split between private vehicles and public transport of 82 and 18%, respectively. We further assume that the observed reduction in $CO_2$ emissions results from a modal shift from private vehicles to public transport. An 8.3% reduction in $CO_2$ emissions from road transport then implies a corresponding decrease in private vehicle usage by approximately 6.8%.

This decrease is derived from the fact that private vehicles represent 82% of the modal split and thus contribute the majority of emissions reductions (calculated as 82% of the 8.3% reduction). To maintain the overall transport capacity, public transport usage must increase by approximately 38%, calculated by dividing the reduction in private vehicle usage (6.8%) by the initial share of public transport (18%).

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 average increase in public transport usage of around 34% and a 38% increase among residents 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.

Further, we calculate the associated marginal abatement cost of carbon for the policy as the government expenditure per ton of $CO_2$ abated. A simple calculation takes the foregone revenue from ticket sales of around 41 Mio. Euros and compares it to the tons of $CO_2$ emissions abated according to our estimates. The latter are calculated as the counterfactual post-treatment emissions for Luxembourg: $\frac{1}{T_{post}} \sum_{t=T_{pre}+1}^{T} CO_{2}{}_{t}^{tr} / (1 - \hat{\tau})$, where $tr$ indicates the treated unit. With this back-of-the-envelop calculation, we estimate a marginal abatement cost of EUR 114 per ton of carbon. This is, of course, a crude estimate and does not capture the full costs nor the additional non-$CO_2$-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.

Finally, we attempt to reconcile our findings with other studies, particularly those examining the German 9-Euro ticket. This short-term policy was implemented in Germany for three months, from June to August 2022. Its temporary nature may explain why the 9-Euro ticket did not result in a substantial shift away from car usage (Liebensteiner et al., 2024). In contrast, Luxembourg's free public transport policy was introduced as a long-term measure with no specified end date, potentially allowing for more enduring impacts on travel behavior and emissions, as documented in our study. Further, recent work by researchers at the Mercator Institute of Global Commons and Climate in Germany examines the impact of the German 49-Euro ticket, a policy introduced in May 2023 that remains in effect today. Their findings also document a significant shift in traffic from road to rail (Koch et al., 2024). Together, these results emphasize that long-term measures are essential for systematically and meaningfully changing individual behavior and reducing emissions.

# 9 Conclusion

We estimate the causal impact of Luxembourg's 2020 free public transport policy on road transport emissions and find a 8.3% reduction in $CO_2$ emissions. Our analysis remains robust across various models that consider the effects of COVID-19, fuel prices, and commuting patterns. It is further validated through placebo tests, sample restrictions, and fuel tourism analyses. Our findings hold high policy relevance, particularly for policymakers in urbanized, affluent areas with robust public transport networks like Luxembourg. Demonstrating the policy's effectiveness in reducing $CO_2$ emissions, our study highlights the potential of integrating free public transport into comprehensive sustainable transport and urban planning initiatives to meet climate targets and foster a sustainable future.

# Appendix A

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

| | (1) | | (2) | |
|---|---|---|---|---|
| | Coef. | SE | Coef. | SE |
| asinh(cases) | $-0.0300^{***}$ | (0.0032) | $-0.0181^{***}$ | (0.0060) |
| asinh(nvrwfh) | 0.0412 | (0.0303) | $0.1881^{***}$ | (0.0553) |
| asinh(wfh) | $-0.0446^{***}$ | (0.0071) | $-0.0443^{***}$ | (0.0106) |
| log(gdp) | $0.2649^{***}$ | (0.0776) | | |
| ei | $0.0036^{***}$ | (0.0004) | | |
| diesel | $-0.6570^{***}$ | (0.0747) | | |
| petrol | 0.0631 | (0.1274) | | |
| log(frt) | 0.0001 | (0.0081) | | |
| Obs | 822 | | 822 | |
| N | 137 | | 137 | |

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 B

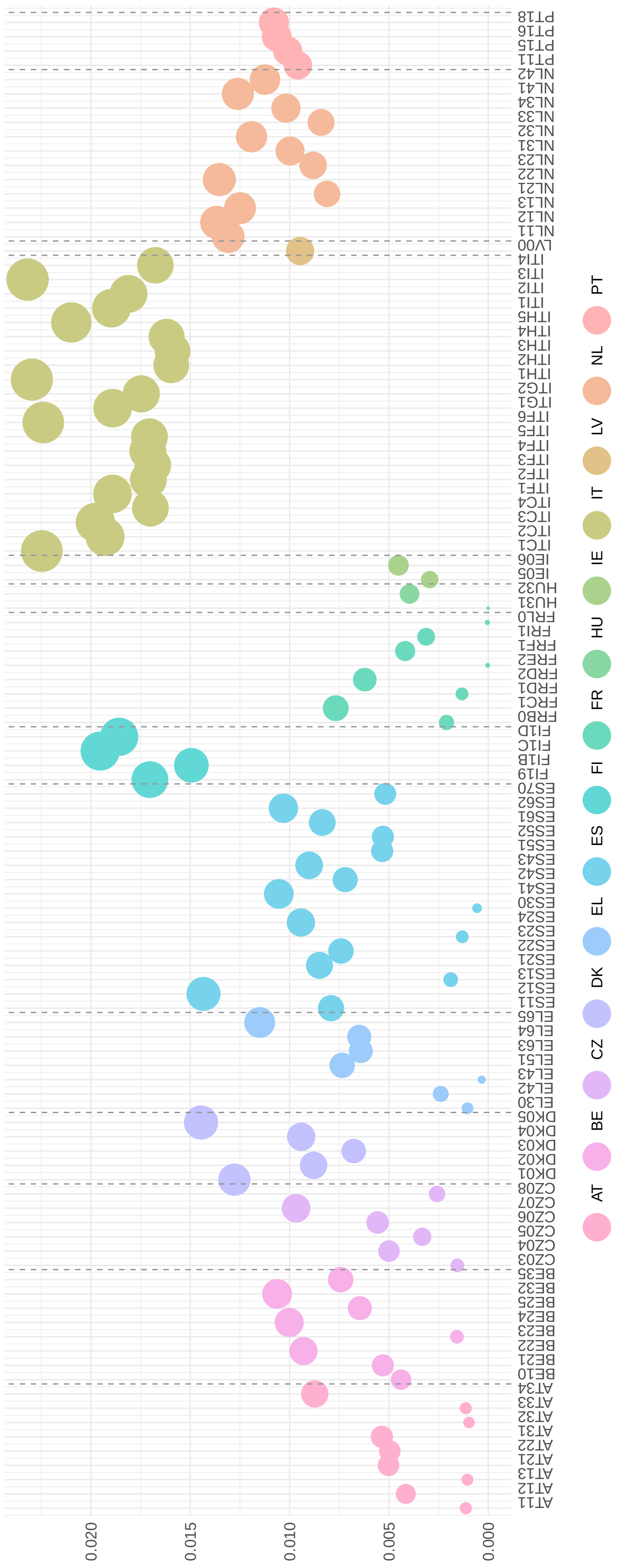
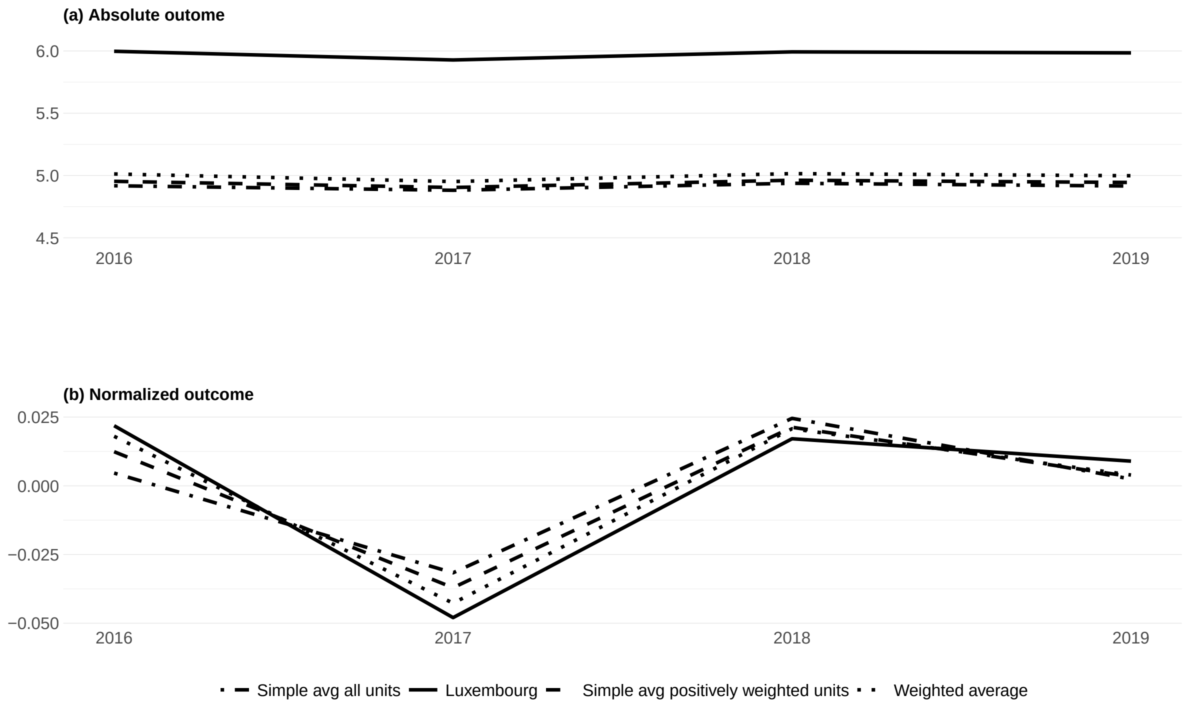



**Figure B.1:** Unit weights - all covariates

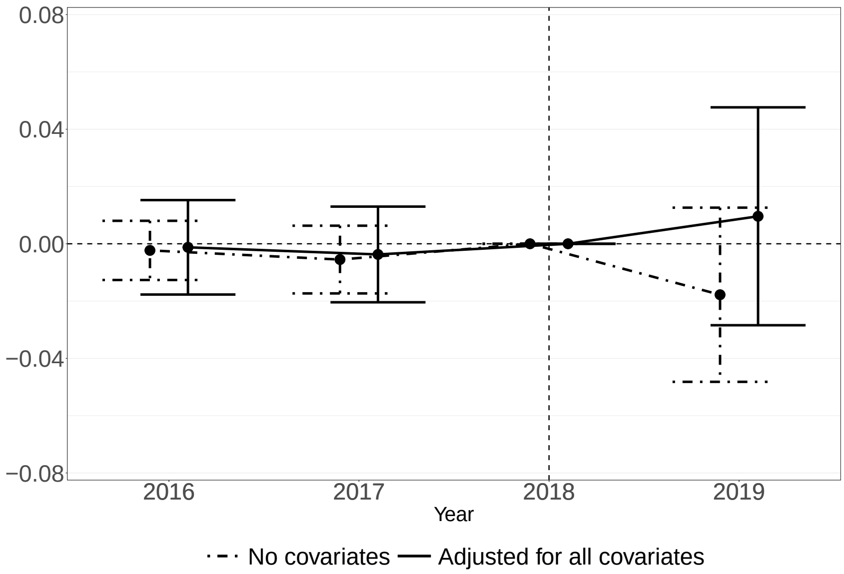
**Figure B.2:** Pre-treatment trends of the adjusted log $CO_2$ per capita emissions




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 C

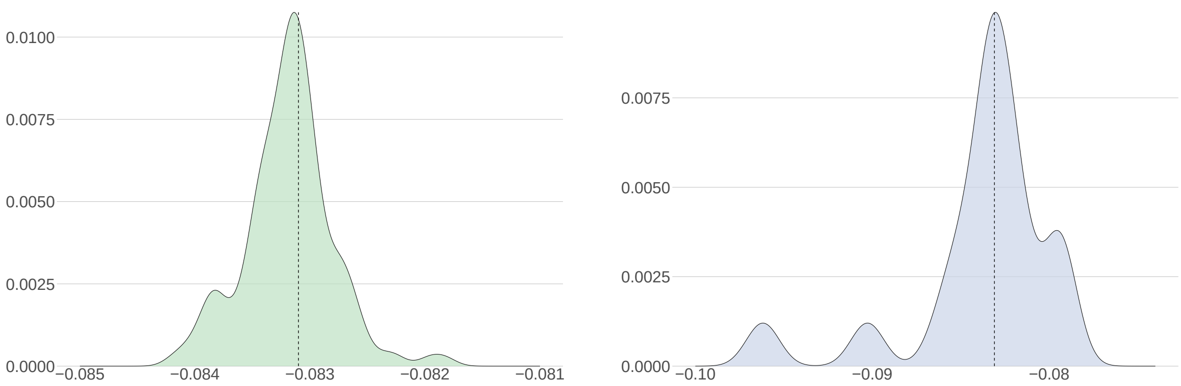
**Figure C.1:** In-time placebo test




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

**Figure C.2:** Distribution of ATT: leave one out analysis

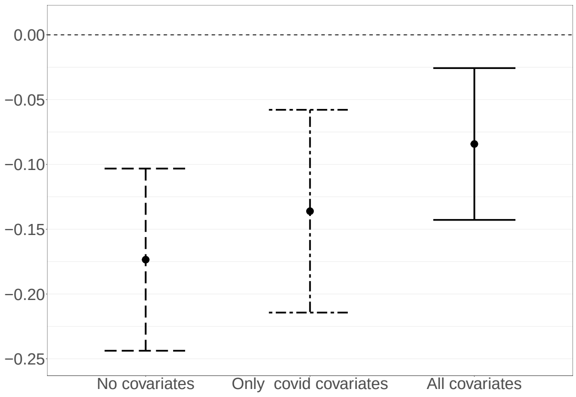
**(a)** Dropping a regions from the donor pool **(b)** Dropping a country from the donor pool



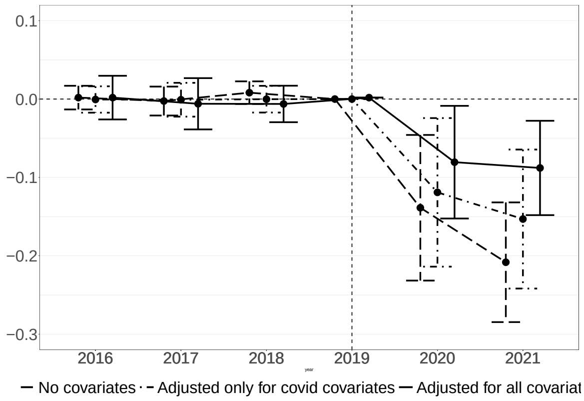

Note: Panel (a) presents the distribution of ATT estimates obtained by iteratively excluding one region at a time and re-estimating the SDID model. Panel (b) displays the distribution of ATT estimates obtained by iteratively excluding one country at a time and re-estimating the SDID model.

**Figure C.3:** ATTs and event study estimates restricted sample

**(a)** ATTs since treatment in 2020

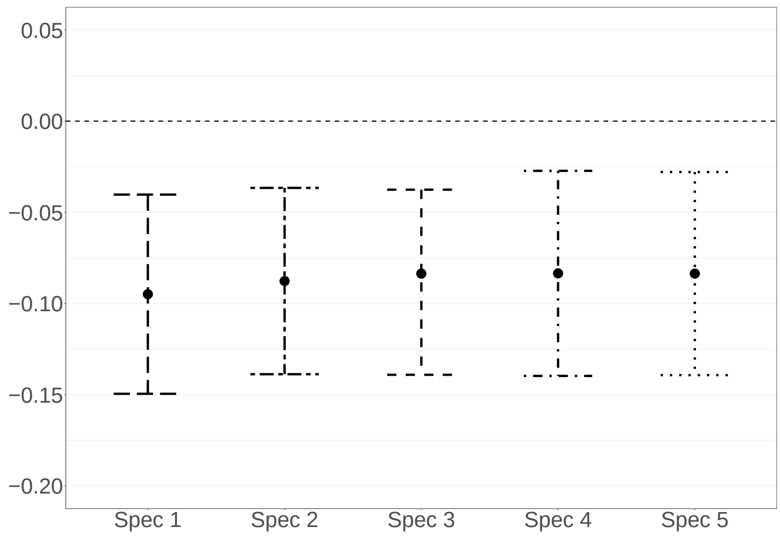



**(b)** Event study estimates for 2016-2021




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 C.4:** 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 C.1:** Sensitivity analysis across different model specifications

| | (1)<br>lco2cap | (2)<br>lco2cap | (3)<br>lco2cap | (4)<br>lco2cap | (5)<br>lco2cap |
|---|---|---|---|---|---|
| acases | -0.0300*** | -0.0296*** | -0.0294*** | -0.0306*** | -0.0306*** |
| | (0.00315) | (0.00305) | (0.00303) | (0.00327) | (0.00320) |
| lgdp | 0.265*** | 0.268** | 0.270** | 0.259*** | 0.259*** |
| | (0.0774) | (0.0946) | (0.0942) | (0.0770) | (0.0768) |
| anever_all | 0.0412 | 0.125*** | 0.125*** | | |
| | (0.0301) | (0.0354) | (0.0353) | | |
| ausual | -0.0446*** | | | -0.0479*** | -0.0479*** |
| | (0.00715) | | | (0.00662) | (0.00662) |
| ei | 0.00359*** | 0.00304*** | 0.00304*** | 0.00366*** | 0.00366*** |
| | (0.000383) | (0.000390) | (0.000389) | (0.000380) | (0.000380) |
| diesel_real | -0.657*** | -0.650*** | -0.653*** | -0.670*** | -0.671*** |
| | (0.0738) | (0.0765) | (0.0759) | (0.0736) | (0.0726) |
| super_real | 0.0631 | -0.0115 | -0.0101 | 0.0635 | 0.0639 |
| | (0.127) | (0.129) | (0.129) | (0.127) | (0.126) |
| lload | | 0.00314 | | 0.000612 | |
| | | (0.00741) | | (0.00780) | |
| Observations | 822 | 822 | 822 | 822 | 822 |

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

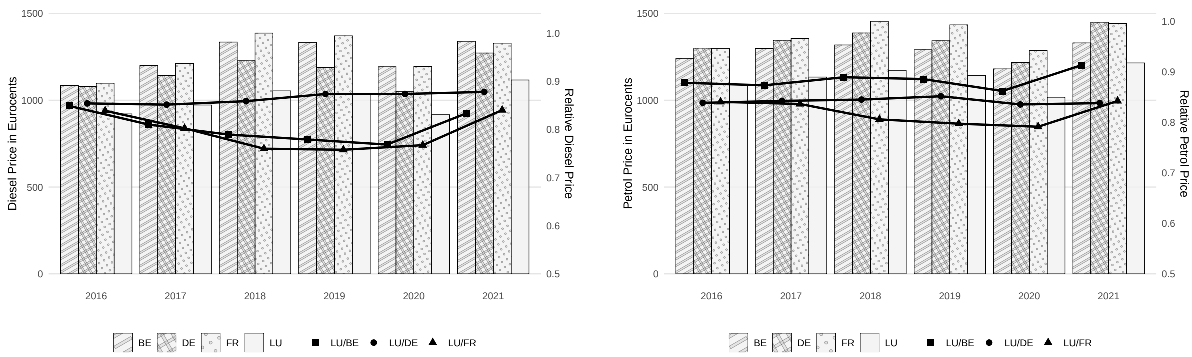
**Table C.2:** Pre- and post-treatment averages of relative fuel prices for Luxembourg

| | Diesel | | Petrol | |
|---|---|---|---|---|
| | Pre-Avg | Post-Avg | Pre-Avg | Post-Avg |
| BE | 0.7825 | 0.8028 | 0.8869 | 0.8814 |
| DE | 0.8684 | 0.8759 | 0.8493 | 0.8368 |
| FR | 0.7585 | 0.8056 | 0.8001 | 0.8182 |

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 C.5:** Absolute and relative fuel prices for LU and neighbouring countries

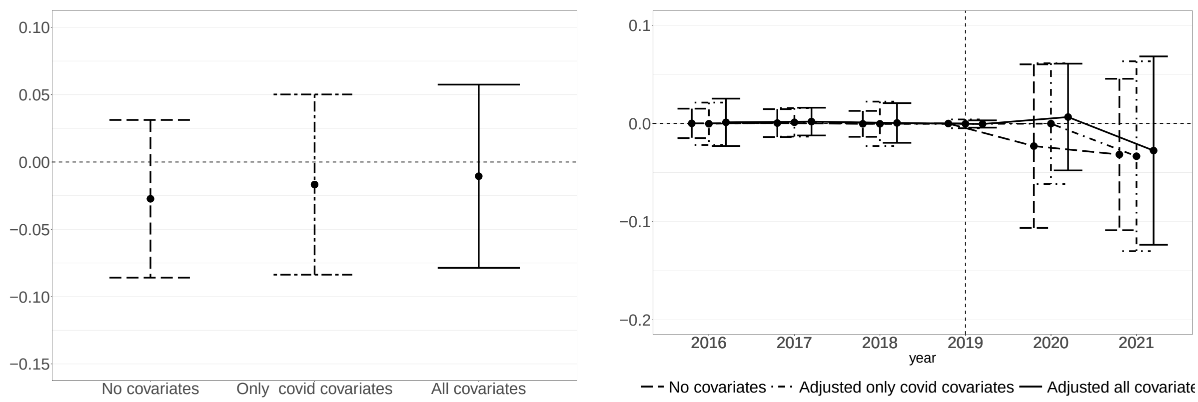
**(a)** Diesel **(b)** Petrol




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.

**Figure C.6:** Energy use in the building sector

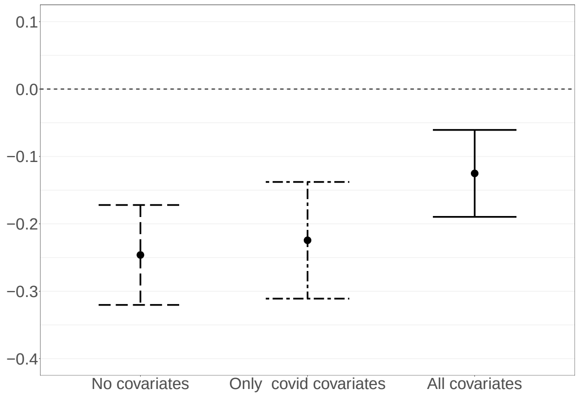
**(a)** ATT since treatment in 2020 **(b)** Event study estimates for 2016-2021



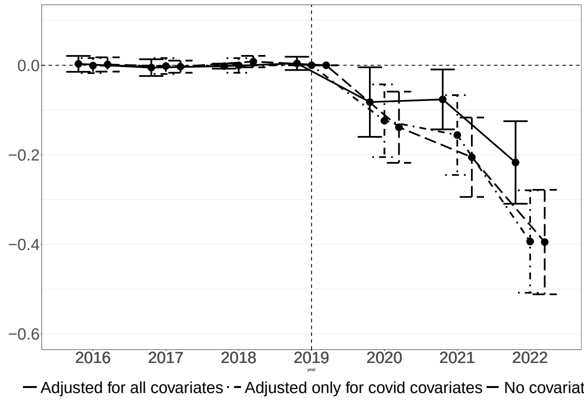

Note: ATTs and event study estimate of the estimated impact of COVID-19 on $CO_2$ emissions from the Energy use in the building sector. The specification with all covariates includes controls for the log of GDP per capita, commuting, working from home, COVID-19 cases, and additionally employment rate.

**Figure C.7:** Extending the post-treatment period to 2022

**(a)** ATT since treatment in 2020




**(b)** Event study estimates for 2016-2022




Note: The sample used for the extended post-treatment period has 129 regions (instead of 137). We lose 8 regions, 6 from Greece (EL42, EL43, EL51, EL63, and EL64), and 2 Italian regions (ITC4, and ITF2) due to missing data in covariates).