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**IN DEFENCE OF FREE RIDING – EVALUATING THE IMPACT OF
DUNKERQUE’S FARE FREE PUBLIC TRANSPORT POLICY ON
USAGE**

Dissertation submitted by

MARIUS VON FRANKENHORST

in partial fulfillment of the requirements for the degree of

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(MMAPP)**

SUPERVISORS: Anand Murugesan, Pablo Pareja Alcaraz

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Author's name and surname(s): Marius von Frankenhorst

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Abstract

Does the introduction of Fare-Free-Public-Transportation (FFPT) lead to higher usage? The recent uptick of municipalities considering and/or implementing such policies to increase the attractiveness of public transportation (PT) vis-à-vis the ever-dominant car suggests that some think so. However, the potential of FFPT to contribute to these goals remains contested, with a common argument being that pricing constitutes only a second-best lever to influence travel behavior next to measures increasing PT-supply or the cost of car-usage. However, causal studies estimating the impact of FFPT-implementation on PT-usage remain relatively sparse. This study contributes to the discussion by causally estimating the impact of staggered (partial-) FFPT introduction in Dunkerque on the percentage of individuals commuting to work by Bus. It models a synthetic Dunkerque to estimate how the modal commuting split would have developed in absence of FFPT-implementation on Weekends (2015), and general implementation together with the inauguration of an overhauled Bus system (2018). It finds a positive annual treatment effect on the share of commutes conducted by Bus of 0.21% (2015) and 0.54% (2018). The findings suggest that this effect is largely attributable to partial-FFPT implementation in 2015 -and thus falls completely on FFPT. The study finds some evidence that the increase in commuters taking the Bus is explainable by a coinciding decrease of drivers, indicating that FFPT may have induced a substitution-effect. While generally robust to in-space placebos, possible sensitivity of the model(s) to in-time placebos caution against a too confident interpretation of results.

Key Words: *Free-Fare-Public-Transportation, Modal transport split, Urban mobility, Commuting behavior, Causal inference*

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1. Introduction

While seeking election for mayor of the northern French municipality of Dunkerque in 2014, the promise of completely overhauling and expanding the cities inadequate Bus-network constituted a key pillar of Patrice Vergriete election campaign (Dairaine, 2019; Urbis Le Mag, 2015). Not only that, but the new network would be completely free, as Vergriete further promised to abolish Bus fares (*Ibid.*). Indeed, he won the election and partially fulfilled the later promise even before the inauguration of the new network, with Bus rides in Dunkerque becoming free on Weekends and Public Holidays in September 2015. The envisioned benefits of introducing Fare-Free-Public-Transport (FFPT) where plenty: Following years of economic hardship, citizens would have more money in their pocket, easier access to the city center where they could spend it, and their increased attractiveness would induce more people to substitute their car with a more sustainable option (Dairaine, 2019; Dans, 2019). However, while the need for an overhauled bus system was generally accepted, the planned introduction of FFPT was more controversial. The measure was deemed both financially unsustainable and unnecessary, as citizens in need of transport subsidies were already subject to corresponding programs (Modijefsky, 2018). Indeed, the general usefulness of the measure was called into question. Critics remarked that if at all, FFPT-schemes had proven able to attract passengers in small cities or large towns, with wholly different travel patterns to a city like Dunkerque with its 150 000 inhabitants (*Ibid.*) Indeed, with the exception of Tallinn, virtually all towns with a population exceeding 50 000 had dropped the measure after a while either due to its financial unsustainability or lack of success in significantly changing transport patterns (Briche, 2017; Modijefsky, 2018). Put simply, the effectiveness of FFPT was unproven, so why risk the negative consequences?

The case of Dunkerque provides a good rendition of contemporary discussions on FFPT-policies. To combat congestion and air pollution created by massive volumes of car-traffic in the city, Anne Hidalgo, the mayor of Paris, actively advocated for introducing FFPT in 2018 (Osborne, 2018). However, she faced similar criticisms to those voiced in Dunkerque, with a commissioned feasibility-study finding that FFPT was unlikely to increase PT-usage by more than 6-8%, with most new passengers furthermore likely to transition from walking or cycling, rather than driving (David et al., 2018; Osborne, 2018). More recently, similar doubts have been voiced regarding the apparent success of Germany's new 49-euro ticket granting monthly access to all regional trains across the country; while proponents argue that the

observable increase in passengers -to an comparable scale as with the tickets 9-Euro predecessor- stand testament for the fare-subsidies' success, the passenger association argues that most of these passengers were already previous train users, with the policy hardly impacting car-usage (Spiegel, 2023a, 2023b). Instead of fare-subsidies, the organization argues, Germany needs heavy investments into its train infrastructure increase the attractiveness of its PT-network (*Ibid.*).

While it is broadly recognized that the dominance of cars in current transport patterns across the world result in a multitude of negative externalities ranging from congestion, over air and noise pollution, to wearing down infrastructure (DESTATIS, 2022; European Enviromental Agency, 2022; Ritchie & Roser, 2022), the potential of FFPT as a response tool thus remains heavily contested in both literature and policy-discussions. Indeed, as the discussed examples showcase, it is often understood as second- or even third best option to influence modal transport patterns. Nevertheless, recent years have seen the emergence of more cities -or with Luxembourg and Malta, even countries- implementing FFPT, or significantly increasing PT-fare subsidies (Carey, 2022; O'Sullivan, 2022). However, while intensifying, the discussions on the potential effectiveness of FFPT to attract new passengers have thus far seemingly only resulted in a moderate number of causal studies of the matter. Against this backdrop, this study exploits the decision made in Dunkerque, and addresses the following research question:

To what extent did the implementation of (partial) free public transportation in Dunkerque causally influence the modal transport split falling on public transport?

The study is structured as follows: The following section discusses the existing academic and policy-related literature on FFPT-schemes. Next, the case of Dunkerque and the context of its policy are introduced. The analytical section of the thesis begins with a discussion of available data sources and limitations before introducing the employed synthetic control mode methodology. This is followed by an analysis of the results and tests of their robustness, including an estimation of FFPT's treatment effect on other modes of transportation. This is followed by a discussion of results and limitations before the conclusion contextualizes the results.

2. FFPT-schemes in the literature

2.1 Do prices even matter?

In essence, a FFPT-scheme constitutes a transport-subsidy seeking to increase demand for public transport (PT) through lowering its (monetary) consumer-cost to zero. In doing so, Proponents argue that it could induce a so-called Mohring-effect: One of the earliest scholars analyzing the potential effect of lowering public transportation fares, Herbert Mohring argued that disutility associated with public transport mainly stems from 1) fare prices and 2) the monetary value of the time spent travelling, including waiting at stops (Mohring, 1972); thus, a service improvement capable of mitigating this disutility could spark a beneficial self-perpetuating cycle, where the mitigated disutility would induce an increase in public transportation demand, thereby necessitating an increase in supply (e.g. service frequency), which would in turn further reduce disutility through decreased waiting times, thereby leading to a further surge in demand, etc. (Cats et al., 2014; Mohring, 1972). To induce such an effect, introducing FFPT would thus need to increase passenger demand for public transportation.

Indeed, real-world experiences indicate that citizens place a high value on the pricing of PT services, with reducing fare-prices ranking first across different options of improving urban mobility between two surveys conducted across the EU and in Tallinn (Cats et al., 2014; European Commission, 2013). In other contexts, raising fare prices has previously resulted in political turmoil, as for instance the experience of Brazil and Chile showcase (Gabaldón-Estevan et al., 2019; Winter, 2017).

The academic literature, however, remains skeptical of prices constituting a valid lever to induce PT-demand, with such subsidies widely being identified as “second-best” option compared to raising the cost associated with car-usage. Most studies estimate demand for PT to fall with income (thereby classifying PT as an “inferior good”), as for instance evidenced by the comparatively higher share of PT in the modal transport split in developing contexts (David et al., 2018; Hidalgo & Huizenga, 2013). Across all contexts, however, demand for PT-services is estimated to significantly fall with an increasing availability of cars (David et al., 2018; Hidalgo & Huizenga, 2013; Paulley et al., 2006). For instance, Holmgren situates the demand-elasticity for PT connected to the availability of cars to be nearly double that of PT-prices, which remain in the inelastic spectrum (-1,48 vs. -0,75) (Holmgren, 2007). Similarly, various studies (Chen et al., 2011; Holmgren, 2007) view petrol prices as a strong determinant of PT-

demand. Chen et. al. (2011) further reports the interesting finding that public transportation demand-elasticity is strongly asymmetric, with price increases (of gasoline or PT-services) eliciting a strongly negative response, while price decreases having little to no effect. Indeed, the common finding that PT-demand is driven by the presence of groups which either cannot afford a car (students) or are uncomfortable to drive (pensioners) may limit price-elasticity for PT to certain segments of the population (Litman, 2021; Rasca & Saeed, 2022). As a result, most authors argue that increasing the cost of private forms of transportation (e.g. through higher gasoline taxes, higher parking fees in inner-city lots, road tolls etc.) is more likely to produce a substantial increase in public transportation demand than lowering fares (Brechan, 2017; Chen et al., 2011; David et al., 2018; Litman, 2021).

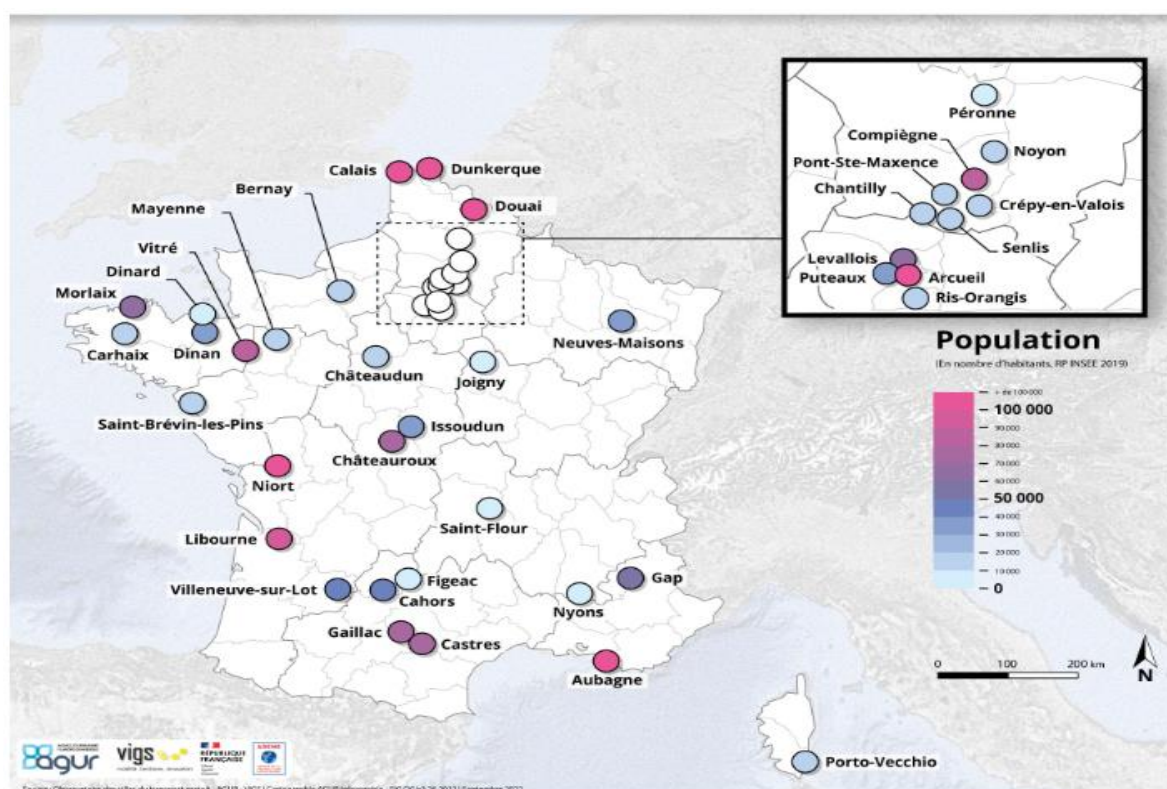
The second-rate nature of pricing-schemes is also thought to extend to other factors influencing PT demand. Generally, supply-factors associated with quality-of-service, such as time spent waiting for and in PT services, service-frequency and availability in terms of distance to PT-stops, and total supply in terms of total distance covered, are thought to exert a higher influence on demand than prices (Brechan, 2017; Paulley et al., 2006; Rasca & Saeed, 2022). More recently, issues such as the perceived safety and sustainability of PT-services have been identified as potentially promising drivers of PT-demand (Punzo et al., 2022; Yannis & Chaziris, 2022); faced with an entrenched preference for cars due to years of car-centric policy and corresponding infrastructure decisions, some authors argue that framing PT as the sustainable and least socially damaging form of transportation may over time provide an avenue through which to induce changes in the modal transport split (*Ibid.*). Expanding the focus to a period of several years then also sees a broader recognition of PT-pricing as a potentially viable tool from scholars viewing cars as a more viable target: It is broadly assumed that both price-elasticity and cross-elasticity with cars rises significantly over time, with decreased PT-fares thereby estimated to be capable of influencing the modal transport split over 5-7 years (Fearnley & Bekken, 2006; Litman, 2021). Furthermore, the considerable variance of elasticity-estimates across study-cases and utilized methodologies, together with the myriad of (non-economic) factors influencing travel patterns, necessitates a careful case-by-case contextualization of results (Litman, 2021; Yannis & Chaziris, 2022).

2.2 Previous FFPT-schemes

First emerging in the 1970's, recent years have seen a renewed interest in FFPT as an extreme form of PT-pricing policy (Gabaldón-Estevan et al., 2019). The majority of FFPT-schemes are however limited to benefit certain groups, most commonly pensioners and students (*Ibid.*).

As of 2018, 97 cities and towns worldwide --most being situated in Europe (56), the USA (27), and Brazil (11) (Kębłowski, 2018)- had introduced “full” FFPT-schemes not subject to such constraints, with Luxembourg and Malta becoming the first countries to do so in 2020 and October 2022 (Ünveren, 2022). France in particular has seen a recent increase in largescale FFPT-introduction. Figure 1 showcases the 39 French municipalities in which as of 2022, PT-services were free-of-charge for all residents, and in many cases also visitors. With the exception of Tallinn and more recently Luxembourg (-city), Calais, Douai and Dunkerque (Rieth, 2021), FFPT implementation not specific to certain groups however remains limited to small cities and/or large towns.

Figure 1 French municipalities with FFPT-schemes in 2022¹



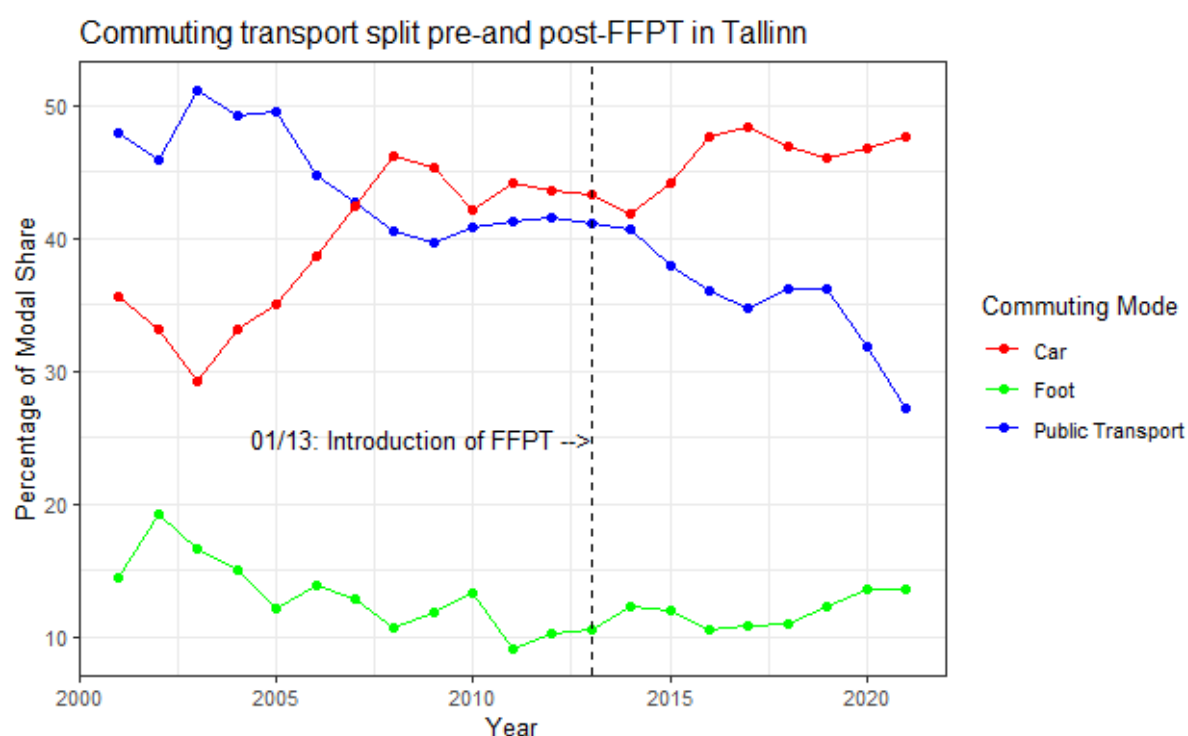
¹ Image taken from: <http://www.obs-transport-gratuit.fr/en/cities-of-free-transport-163/free-for-the-majority-of-users-5094/>.

Like the discussed literature, real-world experiences of FFPT-implementation present a nuanced perspective on their success. To begin with, the general intuition of abolishing PT-fees leading to increased usage seems to hold across different time and geographic contexts: The towns of Hasselt (Belgium, ~75 000 inhabitants, FFPT), Templin (~15 000 inhabitants, Germany) and Aubagne (~ 45 000 inhabitants) all witnessed a dramatic increase in ridership following the introduction of FFPT (Cats et al., 2017; Fearnley, 2013; Tomanek, 2018). However, only the latter experienced success in terms of inducing former drivers to switch to Buses, with only 10-20% of new ridership consisting of former drivers in Hasselt and Templin; instead, the increase in PT-passengers in those cases largely came at the expensive of former pedestrians and/or cyclists (Cats et al., 2017; Fearnley, 2013). While thus not necessarily contributing to more sustainable transportation patterns, the policies also proved financially unsustainable for Hasselt, with the unexpected surge in demand straining the municipalities budget and ultimately leading to the reintroduction of bus fares in 2014 (Cats et al., 2017). The financial unsustainability of the measure has also resulted in the discontinuation of full FFPT-schemes in other municipalities in Spain and Germany (Briche, 2017), contributing to claims that such a policy may only be financially possible in small municipalities (Briche & Huré, 2018; David et al., 2018). Indeed, in Châteauroux, a small French town of 50 000 which introduced free Bus fares in 2001, the increase in passengers and thus service-costs was interpreted differently as being offset through increased labor-mobility facilitating the opening of a new factory in the town center (Deljurie, 2018). Turning to Norway, the cities of Stavanger and Bergen found that the observable uptick in Bus-usage following the removal of fares was either not reciprocated by a decrease in car-usage (Stavanger), or that the reduction of car-traffic in the city center was offset by new trips to PT-stops in the outskirts of town (Bergen) (Fearnley, 2013). While thus successful in attracting new passengers, the make-up of this group consisting of former cyclists and pedestrians, and individuals inherently more dependent on PT-services such as pensioners, young people and recipients of social benefits (Fearnley, 2013; Gabaldón-Estevan et al., 2019) seems to underscore the nature of FFPT policies, and PT in general, as “second-best” option compared to cars.

In comparison to the above, the FFPT policy of Tallinn, introduced in 2013 and targeting a population of 430 000 with access to PT-services other than Buses -namely trams and in-city train rides- stands out and has received more academic attention. Cats et. al. (2014; 2017) find an increase in PT-ridership of 3% within a month of and 14% a year after FFPT-introduction, which however decreases to an estimated 1.2% if controlling for the simultaneous increase in PT-supply through the creation of additional priority lanes for Buses and a general increase in

service frequency. They further find that this increase mainly consists of new commuters from Lasnamae, the citie's district with the highest unemployment rate (Cats et al., 2014). Gabaldón-Estevan et al. (2019) estimate an increase of approximately 10%, but simultaneously note that the usage of (trolley-)buses and trams gradually declined in the post-treatment period. Indeed, figure 2² showcases that when taking the modal transport split of work-commuters as proxy for overall travel patterns, the assumption that FFPT may increasingly influence travel behavior does not seem to hold: While the drop between 2020 and 21 may be attributable to the onset of the COVID-19 pandemic and the connected preference for less crowded modes of transportation, the policy nevertheless does not seem to have been capable of significantly altering the downward trend of PT-usage vis-à-vis cars.

Figure 2: *Commuting transport split in Tallinn 2001 – 2021*



This observation is only somewhat congruent with the findings of other authors; while it may confirm that new PT-users were often unemployed -and thus not captured in the graph- they noted a decrease of overall trips conducted by car of overall 10% following the introduction of FFPT (Cats et al., 2017; Gabaldón-Estevan et al., 2019). Rather than a significant increase in usage, most authors locate the success of Tallinn's FFPT in its social impact, that is an increased accessibility for less affluent citizens, reduced air pollution in the city center and an

² Figure created by Author. Data taken from Statistical Yearbook of Tallinn (Tallinn City Government, 2021). The share of trips conducted by bicycle is not shown as observations were only available for 3 years.

overall increase in satisfaction with PT-services (Ibid.). Notably, the policy was financially sustainable, as its reservation for registered residents increased registrations, thereby expanding Tallinn's tax base (Cats et al., 2014).

While most real-world experiences thus indicate that FFPT can increase passenger demand -with the scope varying from moderate to substantial results-, the “proven” usefulness of FFPT seems to largely incorporate socio(-economic) concerns rather than constituting a measure capable of substantially and sustainably shifting modal transport patterns. Thus, there seems to be little arguments for expanding FFPT-schemes outside of (potentially) socially vulnerable groups who often already benefit from fare-subsidies, particularly given the apparent financial strain caused by FFPT. However, “proven” is here placed in quotation marks as while not detracting from the (methodological) quality of the discussed studies, none of them aimed to explicitly estimate the causal effect of introducing FFPT on PT-usage or other outcomes. That is, while e.g. Cats et. al. (2014; 2017) control for observable PT-supply and socioeconomic factors, they do not account for their possible unobservable counterparts. In light of (recent) literature highlighting factors such as shifting societal beliefs towards sustainability and/or the perception of PT-services as “dangerous” or otherwise unfavorable (see e.g. Punzo et al., 2022), the existence of such unobservable confounders seems plausible, and may therefore bias results.

2.3 Where is the causality?

The logic behind FFPT is intuitive, but is it causally measurable? The discussed academic literature and real-world experiences of FFPT reveals a plethora of (assumed) drivers of PT-demand in relation to pricing. Given this complexity, the need for causal analysis employing methodologies capable of measuring the actual impact of FFPT while accounting for the variance introduced through various (un-)observable factors seems apparent. However, the causal inference literature evaluating the impact of real-world FFPT-policies seemingly remains relatively sparse. Indeed, the discussed causal inference studies specifically dealing with FFPT effects on traffic-related outcomes were only published fairly recently.

One such example comes from Bull et. al. (2021), who employ a randomized control trial (RCT) through randomly assigning a treatment of unlimited travel passes valid across all available PT-services (Buses, Metros, light rail lines) to workers in Santiago de Chile. Following an increase of fare-prices in 2019, Santiago formed the epicenter of country-wide protests ultimately leading to the drive for a new constitution, thereby heavily politicizing the topic (Gabaldón-Estevan et al., 2019). As in other non-high-income contexts, gradual increases

in average household income and car availability had gradually shifted the modal transport split from PT to cars in recent decades (Bull et al., 2021; Hidalgo & Huizenga, 2013). They find that compared to the baseline, workers receiving the free pass on average conducted 12% more trips in total, which however are made up of both PT and non-motorized (walking and/or cycling) trips, of which only the latter is deemed statistically significant (Bull et al., 2021). Furthermore, they find that the treatment effect is completely explained by individuals living within 1km of a metro station, and by trips conducted during less busy off-peak hours, in which the treatment resulted in 23% more non-motorized and PT trips (both statistically significant) (*Ibid.*). In contrast to Cats. et. al. (2017), they find no evidence for travel-mode substitution between pedestrians and PT-users (*Ibid.*). While thus finding a positive treatment-effect on PT-usage causally attributable to FFPT, these findings reiterate the importance of supply factors in terms of PT accessibility and -potentially- quality in the sense of overcrowdings.

While not dealing with PT-demand specifically, previous RCT-designs employed by Phillips (2018) and Banerjee & Sequeira (2023) indicate that randomly assigning PT-fare subsidies across young and/or low-wage job seekers. Specifically, treated clients of an employment agency active in the low-wage labor market in Washington DC on average applied to and interviewed for 19% more jobs (Phillips, 2014). Likewise, young jobseekers in Johannesburg (South Africa) significantly increased the geographical scope of their job search activities when randomly assigned with a transport subsidy (Banerjee & Sequeira, 2023). Both studies thus indicate a direct causal linkage between FFPT and travel patterns, which also seems to mirror the real-world (but not causally studied) experience of Châteauroux discussed above. Nevertheless, the specific nature of outcomes studied cautions against generalizing their findings to the general effect of FFPT on usage.

Finally, the -seemingly- only available causal inference study on outcomes stems related to PT-subsidies stems from Gohl & Schrauth (2022), which employ a quasi-experimental Differences-in-Differences (DiD) design to estimate the impact of Germanies' 9-euro ticket on Air pollution across different municipalities. They find that in the treatment period, the index measuring Nitrogen Dioxide (NO₂) and Particulate Matter (PM) fell by on average 6-7% when compared to the pre-treatment period, with the effect being especially pronounced on weekdays in heavily urbanized areas with higher access to PT-services (*Ibid.*). Given that both air pollutants included in the index are directly linked to fuel combustion, their findings indicate that the 9-Euro ticket contributed to some commuters substituting car with PT-rides.

Furthermore, the findings again highlight the important role of PT-supply for fare subsidies to take effect.

While somewhat limited in scope, the available causal inference literature thus seems to provide a clear indication that subsidizing PT-fares can increase usage, although under the condition that corresponding services are available and accessible. Given that all discussed studies concerned metropolitan contexts of several million inhabitants, and/or estimated the highest treatment effect within heavily urbanized contexts featuring high PT-supply, generalizing their findings to smaller urban areas with comparatively limited PT-services invites the possibility of bias (David et al., 2018). To this end, studying the case of Dunkerque, a city of ~150 000 inhabitants featuring a PT-system consisting solely of Buses- provides the opportunity to expand the causal analysis of FFPT-effects to the context of mid-sized cities.

2.4 The case of Dunkerque

2.4.1 Context – Overhaul yes, but for free?

The introduction of FFPT in Dunkerque came in two steps: Following an initial pilot project making Buses fare-free on Weekends and Public Holidays in September 2015, the complete removal of Bus fares in September 2018 made Dunkerque the then largest European municipality to introduce a full FFPT-scheme -regardless of residency or other factors. Titled *DK Plus de Mobilité*³, the plan to introduce FFPT and revamp the cities' Bus-network formed part of the larger *Projet Phoenix*. This project also encompassed other (economic) measures to revitalize the municipalities ailing center as name-giving Phoenix, such as free 20-minute parking and mandatory façade cleaning (Huré & Delevoye, 2019; Urbis Le Mag, 2015).

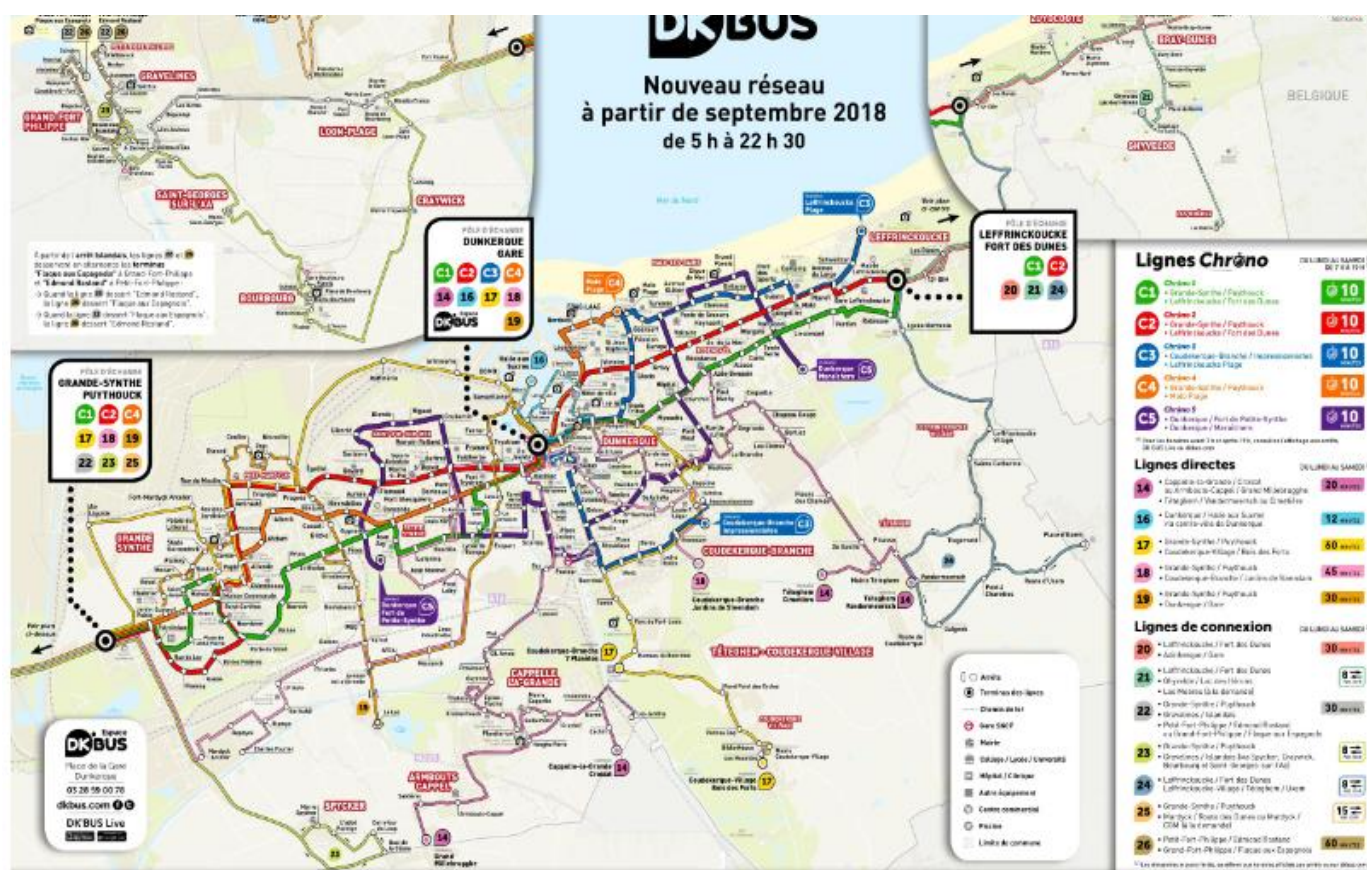
These measures came as a response to years of economic decline. The urban conglomeration of Dunkerque, comprising of 17 municipalities⁴ in close proximity, had experienced a long period of narrowing economic possibilities and increasing unemployment, thereby contributing to an average annual population decline of 1100 residents since 1999 (Briche & Huré, 2018; Modijefsky, 2018). The existing Bus-network and its inadequacy to enhance mobility between Dunkerque's constituent municipalities and the center was deemed

³ The projects website is available here: <https://dk-mobilite.fr/>.

⁴ When speaking of the "municipality of Dunkerque", this study thus refers to the conglomerations' administrative urban authority under this name.

partially responsible. Having failed to keep pace with urban developments, stops excluded many newer neighborhoods, thereby limiting accessibility for many citizens (Dairaine, 2019). Taking the Bus was also unreliable and inefficient compared to driving, with Bus-trips from one of the municipalities to the center on average taking twice as long as driving (30 vs. 15 minutes), a problem that was further exacerbated by congestion in peak hours further slowing down buses (*Ibid.*). Despite over 25% of households not owning a car, 60% of the modal transport split thus fell on drivers (Modijefsky, 2018). Along with FFPT-introduction *DK Plus de Mobilité* thus encompassed a complete overhaul and significant increase in PT-supply: This consisted of raising the total number of Buses and service lines from 10 to 17, a further spread of stops to place 60% of residents within 300 meters of one, the introduction of dedicated Bus lanes to increase service speed, and an increased service-frequency of on average one Bus arriving every 10 minutes (Dairaine, 2019; Modijefsky, 2018). Figure 3⁵ depicts the overhauled system inaugurated in September 2018.

Figure 3: Dunkerques overhauled Bus network



⁵ Figure taken from Briche & Huré (2018): p.3.

In this context, the introduction of FFPT was envisioned to increase the attractiveness of the overhauled Bus-system, with free PT on Weekends and Public holidays serving as an initial “appetizer” (Dairaine, 2019; Dans, 2019). Moreover, it aimed to increase the general mobility of non-car owners and raise purchasing power through lowering transportation costs (Briche & Huré, 2018; Deljurie, 2018). Next to economic considerations, encouraging more sustainable transport patterns by doubling the share of total trips falling on Buses to 10% by 2020 also constituted a policy-goal of the overall project (Briche, 2017; Dairaine, 2019). However, while plans to overhaul the Bus-system did not result in significant resistance, introducing FFPT specifically was criticized as a political rather than outcome-oriented move, with specific arguments largely following the drawbacks of FFPT discussed above: The financing of the policy, which falls on businesses with more than 11 employees via a newly introduced tax, was deemed counterproductive to the goal of reinvigorating the economy as it would further decrease the competitiveness of local businesses (Modijefsky, 2018). Secondly, the need for subsidizing all PT-users was contested, as fare-subsidies specifically targeting economically vulnerable, low-income citizens already existed (*Ibid.*). Above all, however, critiques questioned the general ability of FFPT to attract new passengers, specifically those who were currently using cars, citing the questionable and unproven impact the introduction of FFPT had had in other contexts (Briche, 2017; Modijefsky, 2018).

2.4.2 Previous Evaluations

With the *DK Plus de Mobilité* project explicitly framing Dunkerque as a “laboratory” for the introduction of FFPT, both the partial and full implementation of the policy (in the later case including the revamped Bus system) were accompanied by qualitative evaluation studies. While thus mostly based on interviews and/or surveys to uncover the socioeconomic mechanism behind observed outcomes, they also (non-causally) estimate the quantitative impact of FFPT-implementation on usage (Briche, 2017; Huré et al., 2019).⁶

Following the introduction of partial FFPT, 59% of survey respondents reported an increased usage of Buses (with 49% reporting an increase usage specifically on Weekends) (Briche, 2017). Indeed, a comparison of total passenger numbers during weekdays and weekends between January-February 2015 and 2017 yields an increase of respectively 29%

⁶ While the scope of both studies also encompasses outcomes such as vandalism or financial sustainability, the discussion here focuses on outcomes immediately related to (quantifiable) travel patterns.

(Saturday) and 78% (Sunday or Public Holidays) on days on which FFPT applies, while weekday numbers remain constant (*Ibid.*: 41). Briche finds that the greatest number of new passengers consists of families with children (65,3%), individuals reporting to face economic hardship (67,1%), and/or pensioners (37,5%), thereby rendering (economically) vulnerable groups as one of the greatest beneficiaries of the policy (Briche, 2017; Briche & Huré, 2018). With a majority (68%) of respondents indicating that they substituted car with bus trips on weekends, mainly due to not having to find a parking spot, Briche also finds some indication for a small modal transport split towards more sustainability (*Ibid.*).

Following the full implementation of FFPT (and the inauguration of the new Bus-network) Huré et. al. (2019) find that compared to 2014-15 outcomes, the total number of bus passengers increased by 65% on weekdays, and by 135% and respectively 190% on Saturdays and Sundays. 32% of survey-respondents indicated that they would now use PT-services much more frequently, with 18% increasing their use by a little (*Ibid.*). Moreover, responses indicated a considerable impact on the modal transport split, with 48% of respondents substituting prior car trips with buses, compared to 21% and 11% for pedestrians and cyclists (*Ibid.*). Former pedestrians reported that they now rode the Bus due to the decreased cost, with increased accessibility via newly created stops playing a secondary role (*Ibid.*), thereby indicating a relatively larger impact of FFPT compared to supply factors in this specific context.

While not aiming to causally link the observable results to (partial) FFPT implementation, both evaluations indicate a considerable increase of service-demand in the post-FFPT period. The following sections present the assumed causal framework and the methodology employed to corroborate these findings through a causal inference framework.

3. Causal Framework & Hypothesis

This study aims to contribute to the growing discussion on the potential of FFPT-policies to change modal (urban) transport patterns towards public transportation through estimating the causal impact of Dunkerque’s staggered introduction of partial (“soft”) and full (“hard”) free public transportation. Should -as its proponents argue- the introduction of FFPT indeed reduce barriers and provide a strong incentive for more individuals to travel by public transportation, the following should be observable following its introduction in Dunkerque:

- **H1:** *Introducing free public transportation increases the share of trips conducted by the covered public modes of transportation (Buses, in the case of Dunkerque).*

Figure 4: Assumed causal mechanism between FFPT-introduction and PT-usage

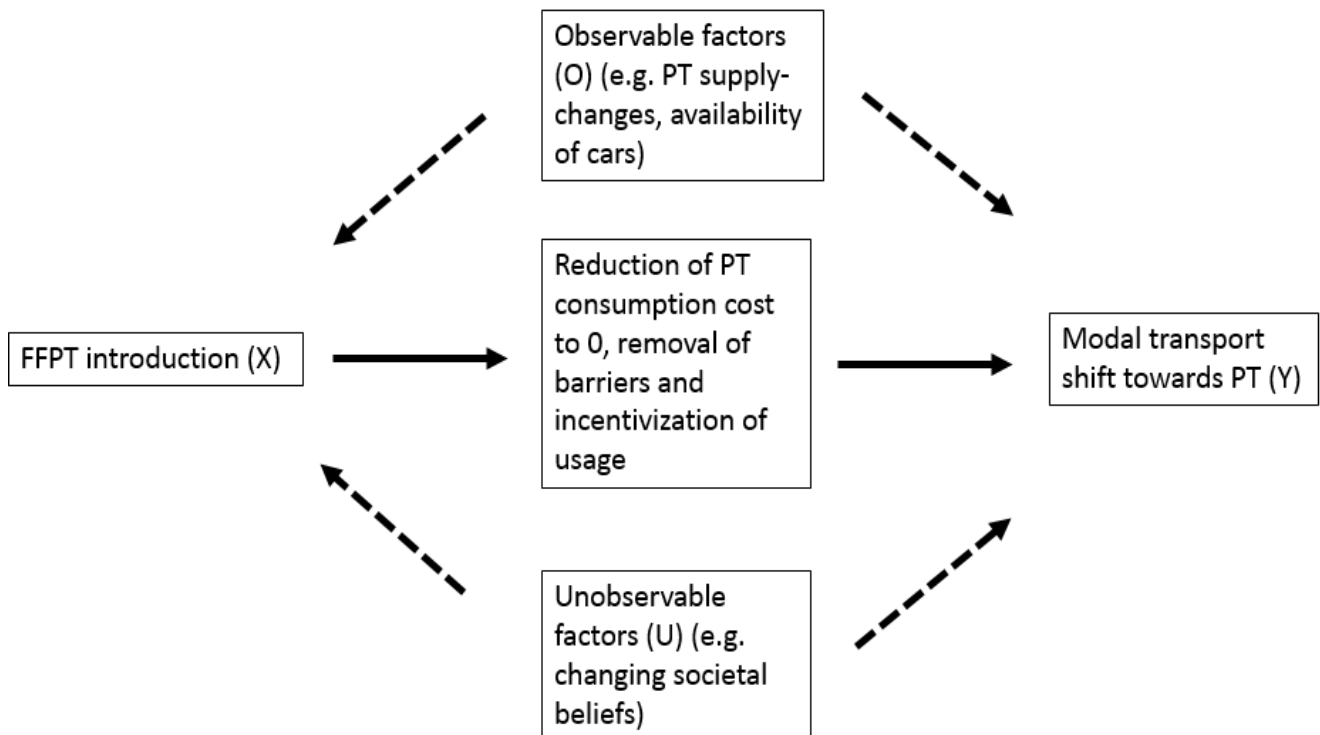


Figure 4 illustrates the -simplified- assumed causal graph underlying the hypothesis. Due to the complex and varied nature of (un-)observable factors associated with the modal

transport split, the depicted relationship in Figure 4 should not be understood as a comprehensive illustration of the underlying process, but rather as an approximation focusing on the assumed effect FFPT can have in this context. The possible presence of (un-)observable factors confounding the relationship between X and Y also renders a “simple” observation of public/ private transportation shares pre- and post-introduction of a FFPT-policy incapable of establishing the causality of its effect; apart from observable factors mentioned in the existing literature -such as income levels and/or the availability of cars- (see e.g. Hidalgo & Huizenga, 2013)- un-/hard to observe factors such as the perceived safety of PT services and/or infrastructure, or an increased societal consciousness regarding the sustainability of different transport modes (Punzo et al., 2022), may all influence individual transport choices.

To untangle the specific causal effect of (partial) FFPT introduction in Dunkerque, this paper employs a synthetic control method (SCM), thereby aiming to utilize a combination of predictors for PT-demand across a series of French municipalities similar to real-world Dunkerque to create a synthetic counterfactual assumed to depict how the modal transport split would have developed in absence of (partial) FFPT introduction. The staggered implementation of FFPT here offers the additional benefit of first causally estimating the effect of partial FFPT in the absence of an increase in supply, which is relatively unique compared to previous implementation e.g. in Tallinn (Cats et al., 2014). Before discussing the application of SCM and utilized data, one should note that the study of FFPT-schemes merely covers an extreme end of transport-price subsidies; as for instance the experience of Germany with its 9/49 euro ticket(s) has shown (Gohl & Schrauth, 2022; Spiegel, 2023a), partial -albeit substantial- reductions of public transport prices may also carry significant potential to increase their usage. Since such interventions are likely based on similar considerations to those depicted in Figure X, the findings of this paper also partially contribute to this discussion.

4. Data & Methodology

This section discusses the available data sources, their limitations, and the approach to mitigate them. Following an identification of viable predictor and control municipalities, it then discusses the intuition behind the synthetic control method and its application to this study.

4.1 Data

To find a suitable synthetic counterfactual depicting how the modal transport split in Dunkerque would have developed in absence of the introduction of FFPT, transport-related data from comparable municipalities is necessary. This study builds on a combination of different datasets stemming from Eurostat's *Cities and Greater Cities* repository⁷, which covers over 900 municipalities across the Union's member states. Specifically, data from the *Transport*, *Population*, *Labor Market*, and *Living Conditions* datasets is utilized to cover variables directly measuring transport patterns, as well as obtaining potential predictors associated with PT-usage.

However, given that Eurostat relies on Municipalities and/or national statistical agencies to report observations of the covered variables, the actual availability of data varies highly between countries and municipalities. While French municipalities are among the most constant reporters, the next section thus briefly covers the steps undertaken to prepare the data for SCM implementation.

4.1.1 Data Preparation

In total, the *Cities and Greater Cities* repository includes Data from 64 French municipalities, which report relatively consistently from 2007 to 2019, with most missing observations occurring sometime between 2008 and 2010 and no data being available after 2019. As the *synth* package utilized for constructing the later synthetic control necessitates balanced data -that is, complete data frames featuring the same number of observations across treatment and control units (Hainmueller & Diamond, 2023) -, it was necessary to impute missing values. This was done via time-series imputation, with a description of the approach provided in Annex I.

To not introduce unnecessary bias through the imputation of missing values while retaining a maximum of available data, the decision was made to not consider French

⁷ All datasets are available through the Eurostats website:
<https://ec.europa.eu/eurostat/databrowser/explore/all/general?lang=en&subtheme=urb&display=list&sort=category>.

municipalities (e.g. Paris) which only started reporting to Eurostat from 2010, and exclude observations after 2019 from the analysis. While the later decision precludes the study of the medium-term effects especially of Dunkerque's full FFPT-policy introduced in 2018, it appears hardly defensible to base any claims on its estimated impact on data imputed from a real-world observation three years in the past.⁸ To further ensure that the analysis does not build on largely imputed values, the percentage of not recorded (NA) observations for every variable between 2007 and 2019 was calculated. All variables with missing observations in more than 50% of cases were excluded from the analysis.

Most variables included in the analysis featured missing observations in ~15% of cases, with exceptions being made for the median disposable income (*median_disposable_income*, ~31% of observations NA) as well as the average cost of a 5km taxi ride (*cost_5kmtaxi*, ~38% of observations NA). This decision is based on the strong linkage between income levels and PT-usage identified in the literature (see e.g. (Hidalgo & Huizenga, 2013). Similarly, average taxi fares are utilized as closest available proxy to fuel prices (Weinandy & Ryan, 2021). While thus expanding the range of predictors covered in the analysis, the inclusion of both necessitates an especially careful consideration on the predictive weight placed on them in the later analysis. The respective percentage of NA-observations is reported for each variable in table 1 (see table 7 in Annex I for full overview of all initially considered variables and their percentage of NA-observations).

4.1.2 Final Data

Following the exclusion of certain variables based on their availability, table 1 presents the variables utilized for measuring the outcomes of H1, as well as for constructing a counterfactual Dunkerque which never introduced (partial) FFPT. The modal transport split is approximated through the share of trips to work conducted by PT (Buses) (*modal_PT*); while thus not capturing the increase of passengers travelling by Bus for leisure-purposes identified in previous evaluations (Briche, 2017; Huré et al., 2019) -and possibly attributable to the

⁸ Of course, including the years from 2020 onwards would have also meant covering the COVID-19 period and its mobility-limiting response policies in France. Given the dynamically shifting severeness of such policies across time and different municipalities, any analysis of this timeframe would have likely necessitated farther reaching assumptions on the validity of observed results.

introduction of (partial) FFPT- it allows for estimating the treatment effect on daily commuting activities. This may provide valuable insights as daily work-trips tend to constitute a significant portion of the modal transport split and often involve distances necessitating motorized -and reliable- transport options (Rasca & Saeed, 2022). Indeed, the volume and average distance of commuting-traffic has rendered it a prime target for pricing-schemes seeking to incentivize a shift away from cars towards PT (Spiegel, 2023b) and has previously been used by other researchers to capture the treatment effect of FFPT (Bull et al., 2021). Thus, a successful change of commuting behavior would constitute a significant success for FFPT as it would influence a section of transport behavior which is both substantial in size and potentially harder to change compared to “leisure-travel” (Rasca & Saeed, 2022). And while the initial “soft” FFPT-scheme only extended to weekends and public holidays, the variable is still capable of capturing the potential treatment effect on commuters who work on these days.

The predictor variables then constitute factors other than pricing which may influence *modal_PT* outcomes, and are later weighted to construct a counterfactual Dunkerque seeking to capture the pre-treatment trends in both variables as accurately as possible. They are chosen due to existing literature firmly linking them to modal transport trends (*median_disposable income*, *cars_registered_1000pop*, *econ_activity_rate*⁹) (see e.g. (Hidalgo & Huizenga, 2013; Holmgren, 2007; Rasca & Saeed, 2022), with some constituting potential proxies for not directly available factors: As aforementioned, the cost of a 5km taxi ride may approximate trends in fuel prices, while the *average* number of commuters approximates traffic volumes and possible congestion in a municipality. The ratio of traffic deaths to inhabitants may provide insight into the general safety of travel conditions. As Punzo et. al. (2022) note, the perceived unsafety of public transport stops due to unclear demarcations may disincentive citizens from frequenting them. Finally, the percentage of people going to work by foot may provide inside

⁹ The *cars_registered_1000pop*, *traffic_deaths_10000pop* and *econ_activity_rate* variables were calculated through their respective total counterparts and the population variable. Hence, the *econ_activity_rate* is likely underestimated, as it is based on the total population, rather than labor force. Since this is however true across all municipalities, it should not result in significant bias.

into the geographic distance covered by commuters, as a high percentage would indicate a comparatively lesser need for motorized transport.¹⁰

Table 1: Outcome and predictor variables utilized in analysis

Variable	Description	% of NA in Eurostat data
modal_PT	Percentage of trips to work conducted by public transport (Bus)	15.3
modal_car	Percentage of trips to work conducted by car	15.3
number_commuters_in	Total number of daily commuters into the city	15.2
econ_actvity_rate	Percentage of economically active population	15.2
traffic_deaths_10000pop	Ratio of traffic deaths per 10000 inhabitants	8.1
cars_registered_1000pop	Ratio of registered cars per 1000 inhabitants	15.2
cost_5kmtaxi	Average cost of a 5km taxi ride	38.3
median_disposable_income	Median disposable income per household	32

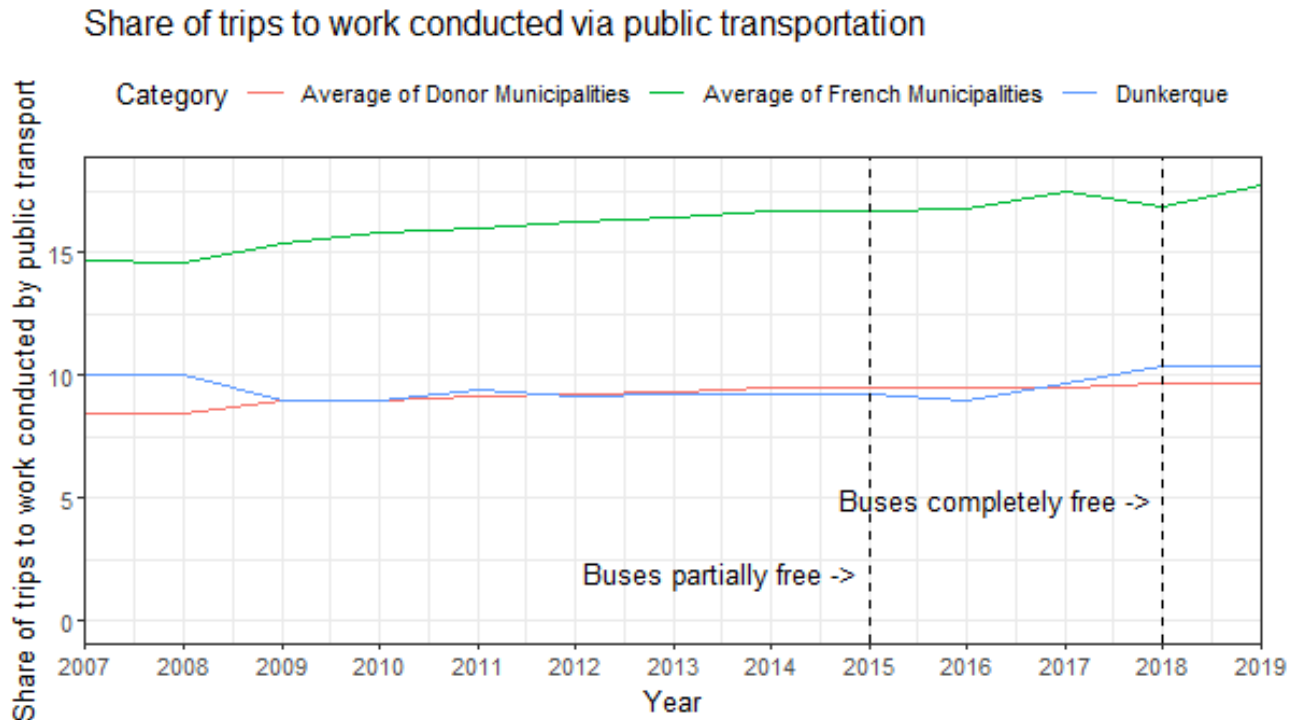
Through constructing a counterfactual to the treated unit via a combination of weighted control cases and predictors, SCM is less reliant on balanced pre-treatment trends between treatment and control group than other quasi-experimental methods (Kellogg et al., 2021). Nevertheless, including control municipalities whose pre-treatment outcome and/or predictor trends differ significantly from the treated unit and/or other controls may infringe upon the convex hull assumption if it renders Dunkerque an outlier compared to the chosen controls (Cunningham, 2021). Their inclusion should thus be avoided to minimize the bias of the SCM especially when -as in our case- only a limited amount of pre-treatment observations to train the SCM are available (Ahmed, 2021; Cunningham, 2021). Thus, a further subset of French municipalities based on their pre-treatment modal commuting split and population was created. Finally, the municipalities of Nîmes and Chambéry were removed from this subset, as both inaugurated revamped bus-systems including new and extended service lines in 2016, thereby implementing a supply-increase treatment possibly influencing their PT-demand (Bourbiaux, 2016; Lachaud, 2016). The final donor pool then consists of 22 municipalities: *Annecy, Arras, Avignon, Bayonne, Brest, Boulogne-sur-Mer, Colmar, Calais, Douai, Limoges, Lorient, La Rochelle, Lens, Martigues, Pau, Perpignan, Toulon, Saint-Brieuc, Troyes, Vannes, Valence Valenciennes*.¹¹ As showcased by figure 5, the mean share of commutes conducted by PT

¹⁰ While also available through Eurostat, *modal_bicycle* was not chosen as a predictor due to ~62% of observations missing.

¹¹ Note that Brest and Valenciennes -unlike Dunkerque- also operate two tramlines each. While thus offering a higher supply of public transportation, they were kept in the donor-pool, under the assumption that their similar (pre-treatment) outcomes in terms of public transportation usage indicate similar underlying transport patterns. To nevertheless preclude bias, whether they are weighted in the later SCM(s) receives special attention, and

develops quite similar between this donor pool and Dunkerque, whereas the mean of all French municipalities available in Eurostat is significantly higher.

Figure 5: *Share of commutes by Bus - France, Dunkerque and donor municipalities*



4.2 The Synthetic Control Method

First introduced by Abadie & Gardeazabal in a 2003 study estimating the impact of conflict on GDP of the Basque Country, SCM has since firmly established itself among the causal inference methodologies (Cunningham, 2021; Hainmueller & Diamond, 2023). Compared to its quasi-experimental counterparts, its main “innovation” consists of the “independent” creation of a counterfactual to the treated unit via calculating and applying a weight-matrix across a group of control units and predictor-variables; through minimizing the distance between itself and the observed pre-treatment outcome of the treated unit, the created (hence “synthetic”) control is then assumed to display the outcome of a counterfactual unit which never received the treatment (Cunningham, 2021). Based on the assumption that a

Annex II includes SCMs produced without them in the donor pool. While the ability to trace the pre-treatment trend between 2007-2010 is inhibited, a similar post-intervention treatment effect is estimated.

synthetic control closely following the observable pre-treatment outcomes of its real-world counterpart should also exhibit similar unobservable factors, the post-treatment divergence between synthetic and real-world outcome trajectory is then interpreted as the treatment effect.

Expressed differently, if $J = 1$ denote Dunkerque, the treated municipality, and $J + 1$ denote the French control municipalities included in the sample ($j2$ to $j = J + 1$), all of which are observed over pre- and post treatment time periods $t = 1, 2, \dots, T0(\text{soft treatment}) + t0 + 1, t0 + 2, \dots T1(\text{hard treatment}), t1 + 1, t1 + 2$ (Abadie et al., 2015; Andersson, 2019); note that the soft and hard treatments here refer to the partial and full implementation of FFPT in Dunkerque. Synthetic Dunkerque then constitutes a vector chosen from the control municipalities ($J \times 1$), and consists of a combination of weighted averages (W) between them: $W = (w_2, \dots, w_{J+1})$, where $0 \leq w_j \leq 1$ for $j=2$ $w_2 + \dots + w_{J+1} = 1$, with every choice of W thereby creating a different estimate of synthetic Dunkerque (*Ibid*). To allow for the estimation of the treatment effect following $T0$ (and/or $T1$, in our case), W is chosen to minimize the difference -and thus maximize the balance- of the predictor-variables between Dunkerque and its synthetic counterpart in the pre-treatment period; to reflect their relative importance in estimating the (counterfactual) outcome, the predictors are also assigned weights (V) (*Ibid*). The literature suggests a range of approaches to choose optimal weights for W and or V , ranging from “manual” selection based on previous findings regarding the outcome variable, to training approaches involving the splitting of pre-treatment data into different folds followed by cross-validation (see e.g. (Abadie et al., 2015)). This study employs an approach based on the joint optimization of country (W) and predictor weights (V), so as to minimize the mean squared prediction error (MSPE) of synthetic Dunkerque for the outcome variable in all pre-treatment observations; thus, the goal of optimization is tracking Dunkerque’s pre-treatment trend of modal_PT/car as closely as possible (see e.g. Abadie et al., 2010; Andersson, 2019) for other examples of this approach).

The “independent” creation of a synthetic counterfactual is widely identified as a major advantage of SCM compared to other quasi-experimental causal inference methods, as it removes the reliance on finding specific control units very similar to the treated unit and/or experiencing parallel pre-trends (Abadie et al., 2015; Andersson, 2019; Kellogg et al., 2021). The modeling of a synthetic counterfactual post-treatment trend further guards against extrapolation bias, as a corresponding counterfactual for every observation in the post-treatment period is created (Abadie et al., 2015; Cunningham, 2021). Finally, SCM also provides greater

transparency compared to regression-based approaches, as the respective weights assigned to control municipalities and predictors is documented for each model (Cunningham, 2021).

However, the relatively small amount of available pre- (and post-) treatment observations may present a challenge for SCM-implementation, as this may inhibit the stability of the estimated synthetic Dunkerque, thereby potentially rendering it sensitive changes in model-specification. Further, it precludes the creation of training and validation periods in the pre-treatment years (Abadie et al., 2010; Cunningham, 2021). Thus, special attention to the robustness of results across the corresponding tests must be paid.

5. Results & Analysis

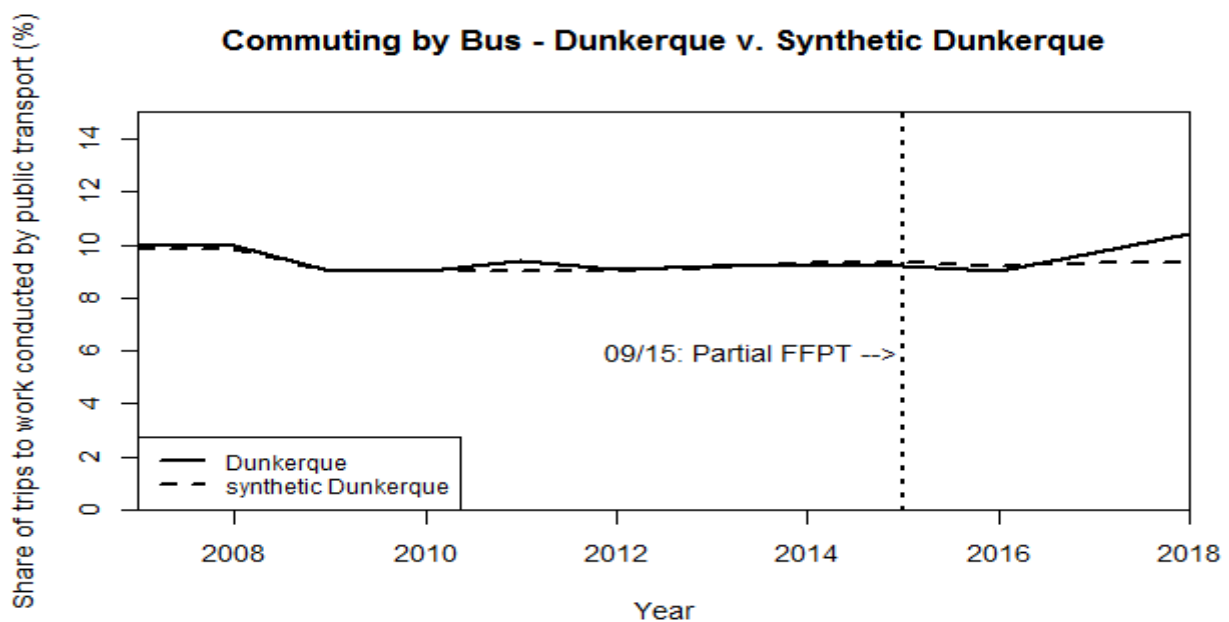
Given the staggered implementation of partial (September 2015) and full (September 2018) FFPT in Dunkerque, the analysis is equally split into two sections. First, the effect of partial-FFPT is estimated through fitting an SCM on the data up to its introduction. Later, an SCM covering both treatments is discussed; while not allowing for a clear estimation of the treatment effect specifically caused by full-FFPT implementation vis-à-vis its partial predecessor and the simultaneous inauguration of Dunkerque's revamped Bus-system, this approach may provide insights into the combined effect of both policies. Following the discussion of both models, several robustness tests via in-space and -time placebos are conducted; this also includes modelling the effects of FFPT on other commuting modes.

5.1 Results

5.1.2 Estimating the impact of partial FFPT introduction

Figure 6 depicts the development of real-world and synthetic Dunkerque regarding the percentage of individuals commuting to work by Bus between 2007 and 2018. While failing to capture the brief increase between 2010 and 2011, synthetic Dunkerque otherwise seems to closely track the trend of its real-world counterpart prior to the introduction of partial FFPT. Indeed, the average yearly distance between both trends is 0.13% in the pre-treatment period.

Figure 6: *Commuting by Bus - Dunkerque vs. Synthetic Dunkerque – 2015 model*



This visual impression is further corroborated by the closeness of Synthetic and real-world Dunkerque regarding their pre-treatment means across the utilized predictors, as depicted in Table 2. While not a perfect match, the averages between Dunkerque and synthetic Dunkerque are much closer than those of the donor municipalities -which themselves tracked Dunkerque's pre-treatment outcome of people going to work by Bus quite closely; thus, synthetic Dunkerque does not only closely track Dunkerque's pre-treatment commuting split outcome falling on Buses, but also accounts for the potential influence exerted on this outcome by the predictor-variables, thereby strengthening the assumption that any post-treatment divergence can be attributed to the introduction of partial FFPT (Abadie et al., 2015; Andersson, 2019).

The respective weights assigned to each predictor (V) further seem to largely follow previous findings discussed in the literature review, with the availability of cars (0.428) constituting the main driver behind PT-usage in this model, followed by income levels (0.267) and the average number of daily commuters (0.214). On the other hand, the modal commuting split falling on pedestrians and the traffic deaths per 10000 inhabitants (both 0.004) hardly play a role, which may also explain the relative imbalance between synthetic and real-world Dunkerque regarding both predictors.

The weight matrix assigned to the donors (W) represents Dunkerque by a combination of seven municipalities, with Lorient (0.33), Lens (0.29), Troyes (0.15) and Douai (0.14) constituting the most relevant donors. This appears reasonable given their relative proximity of Lens to Dunkerque in terms of location (both cities are 100 kilometers apart) and size (~200 000 vs. ~150 000 inhabitants). Lorient, Douai and Troyes are slightly smaller (~100 000 inhabitants), with the first two -like Dunkerque- being coastal towns. The inclusion of smaller cities may also be explained by Dunkerque's lack of PT services other than Buses, and the moderate scope of its Bus network prior to the 2018 overhaul (Dairaine, 2019). Indeed, neither Brest nor Valenciennes -the only donor municipalities featuring trams as additional PT service next to Buses- receive any weight, meaning that their (possibly) greater supply of PT does not bias the SCM.

Table 2: Pre-partial FFPT means

Pre partial	Treated	Synthetic	Donor Pool Mean	Assigned Weights
Number of daily commuters	25321.222	25317.123	28108.919	0.214
Cost 5km taxi ride	11.211	11.199	11	0.038
% Pedestrian commuters	8.022	9.245	10.275	0.004
Economic activity rate	0.424	0.423	0.43	0.046
Traffic deaths/ 10000 inhabitants	0.333	0.199	0.293	0.004
Registered cars/ 1000 inhabitants	455.333	455.992	500.869	0.428
Median disposable income	19246.222	19223.756	20087.061	0.267

Table 3: Weights assigned to municipalities

Weights assigned to Donors	Municipality
Assigned weight	
0.07	Annecy
0.01	Arras
0.00	Avignon
0.00	Valenciennes
0.00	Colmar
0.00	Calais
0.14	Douai
0.00	Limoges
0.33	Lorient
0.00	La Rochelle
0.00	Boulogne-sur-Mer
0.00	Vannes
0.00	Saint-Brieuc
0.15	Troyes
0.00	Martigues
0.00	Valence
0.00	Brest
0.01	Bayonne
0.00	Pau
0.00	Toulon
0.29	Lens
0.00	Perpignan

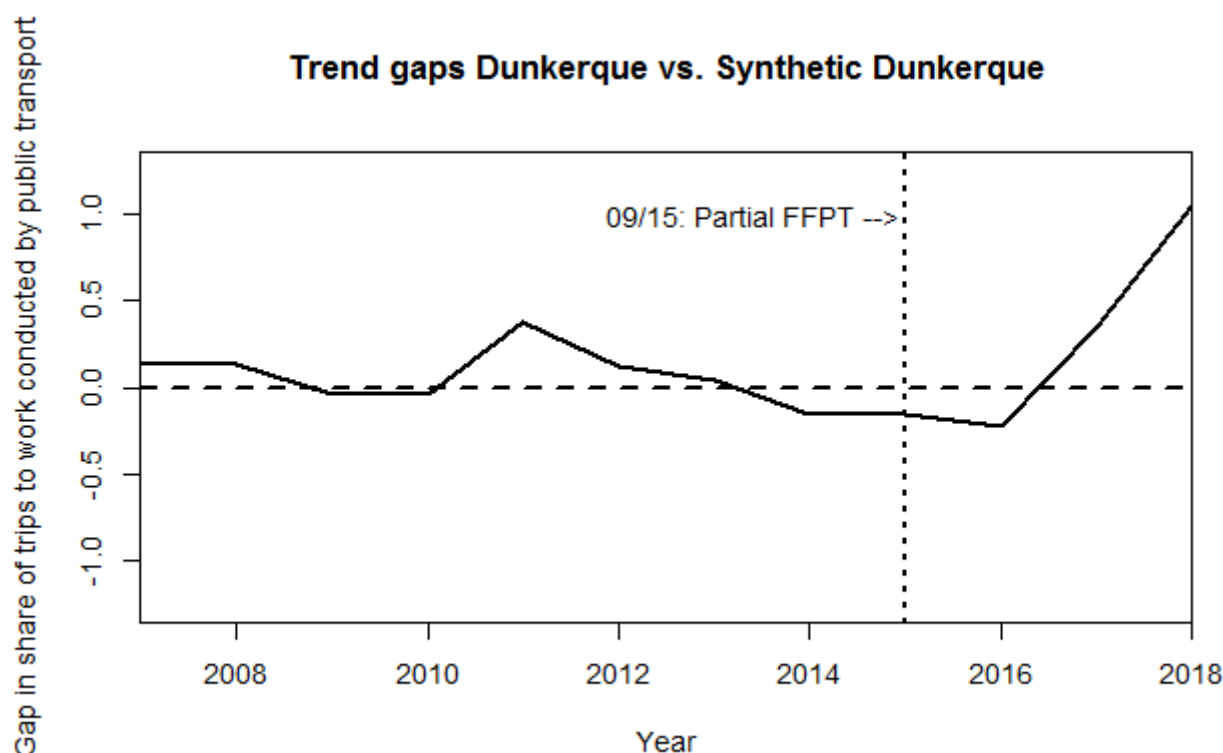
Taken together, the closeness between synthetic and real-world Dunkerque across their observable pre-treatment outcome trends and (key) predictor means supports the assumption that both may also be balanced regarding unobservable (and/or not-included) factors potentially influencing the commuting transport split. Thus, the post-treatment divergence between both may be interpreted as capturing the causal effect of eliminating Bus-fares on Weekends and Public Holidays on usage by commuters (see figure 7 for a clearer depiction of trend gaps). A lagged treatment effect is modelled, with the percentage of Bus-commuters even estimated to slightly decrease in 2015 (-0.15) and 16 (-0.23), before significantly increasing afterwards (0.35 in 2017 and 1.04 in 2018). Across the whole treatment period, the model thus indicates that on

average, the introduction of free Bus rides on Weekends and Public holidays increased the usage for commuting by 0.25% annually. Given that the policy was implemented in September 2015 -and followed by full FFPT in September 2018-, -and assuming the policy should roughly take the same effect across every month- allows for calculating a potentially slightly more precise estimate, yielding an average treatment effect of 0.21%.¹²

¹² Calculation: $\frac{1}{3} * \text{gap}(2015) + \text{gap}(2016) + \text{gap}(2017) + \frac{3}{4} * \text{gap}(2018)$. Of course, this also assumes a “clear cut” between the effects of partial- and full FFPT implementation and should thus only be understood as an approximation.

Before presenting the results of the 2018 model, an initial interpretation: The lagged treatment effect on commuters -compared to the more immediate increase in Bus-usage by leisure passengers identified in the previous (non-causal) study (Briche, 2017)- may potentially be explained by the more habitual nature of commuting trips relative to those conducted for leisure, thereby also posing higher requirements for service-reliability to render PT a preferred commuting-mode (Rasca & Saeed, 2022). As the revamped Bus system was only inaugurated together with full FFPT in September 2018, the perceived unreliability of Dunkerque's limited and out-of-date public transport system may thus have contributed to this lag in commuter-adoption (*Ibid.*). Additionally, the number of commuters on Weekends and (especially) Public Holidays will naturally be lower than during workdays; however, the estimated increase does not seem too excessive to not be coverable by individuals working on these days. However, in the absence of tests of the model's robustness and sensitivity -especially given the short pre-treatment period-, the above should be interpreted with caution.

Figure 7: *Trend gaps Dunkerque vs. Synthetic Dunkerque - 2015 model*



5.1.2 Estimating the impact of full FFPT introduction

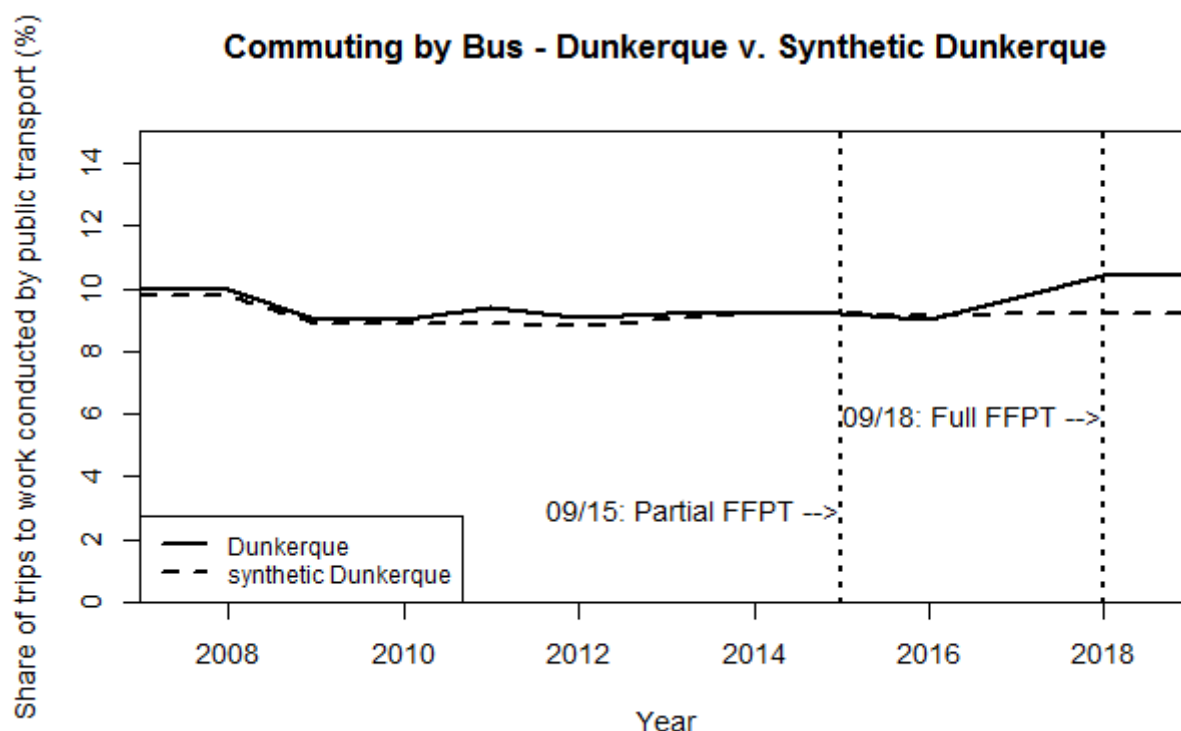
Figure 8 depicts the development of the commuting transport split falling on buses between synthetic and real-world Dunkerque between 2007 and 2019. Again, synthetic Dunkerque initially tracks the real-world trend reasonably well, although less closely than the

previous SCM. It does however track the period immediately preceding partial FFPT-introduction more closely. Up to 2016, the average distance between both trends is thus slightly larger at 0.17, with the trends again diverging immediately after. In terms of pre-treatment balance (Table 4), synthetic Dunkerque again achieves reasonable similarity on the highly weighted predictors, with the possible exception of the average number of daily commuters, where the distance is slightly higher. The relative (un-)importance of the predictors in terms of their assigned weight remains largely the same, with the cost of a 5km taxi ride now hardly playing a role at all.

Table 4: *Pre-full FFPT means*

Pre partial-FFPT means				
	Treated	Synthetic	Donor Pool Mean	Assigned Weights
Number of daily commuters	25410.909	25386.205	28373.579	0.205
Cost 5km taxi ride	11.264	11.274	11.051	0.001
% Pedestrian commuters	7.809	9.3	10.06	0.004
Economic activity rate	0.423	0.423	0.429	0.063
Traffic deaths/ 10000 inhabitants	0.273	0.25	0.26	0.017
Registered cars/ 1000 inhabitants	459.182	459.944	502.351	0.439
Median disposable income	19041.455	19014.591	19899.165	0.273

Figure 8: *Commuting by Bus - Dunkerque vs. Synthetic Dunkerque – 2018 model*



The similarity between the 2015 and 2018 models also extends to the weight matrix assigned across the control municipalities (Table 5); all previously used municipalities are again assigned weight, with the same four -Douai (0.21), Lorient (0.18), Troyes (0.14) and Lens (0.33)- exerting the biggest influence in creating synthetic Dunkerque, although Lens now is the strongest. As only new addition, Boulogne-sur-Mer -a coastal town of 85 000 inhabitants

Table 5: *Weights assigned to municipalities*

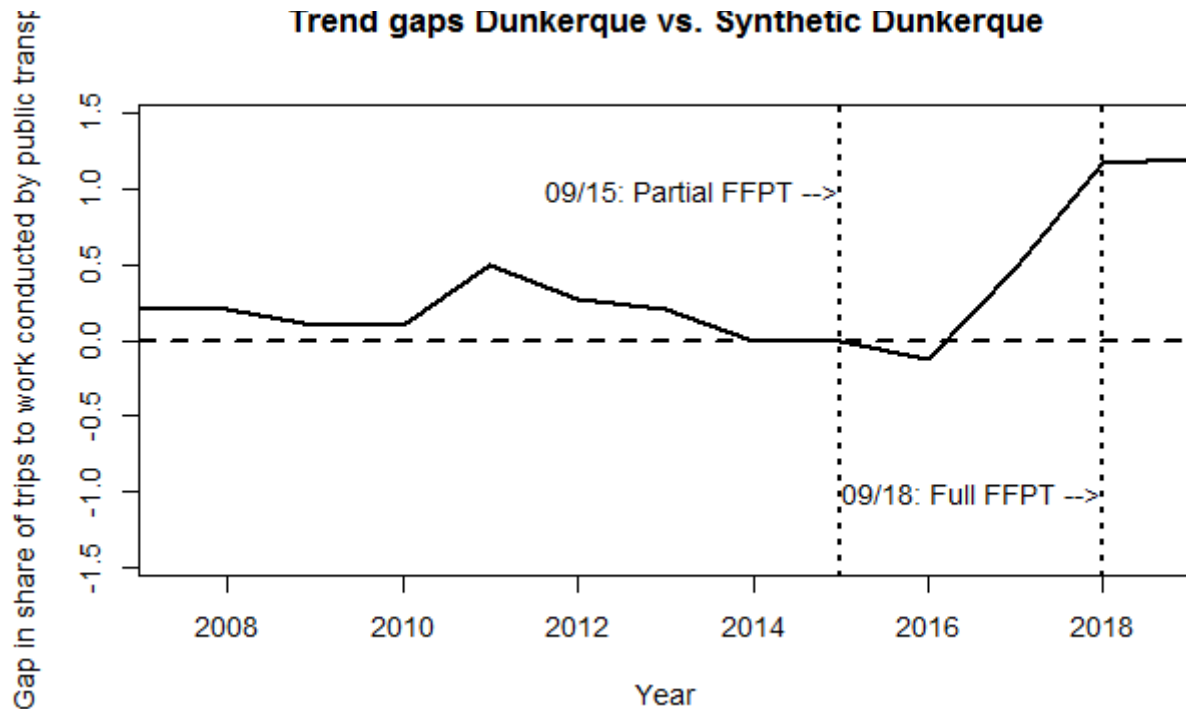
Weights assigned to Donors	
Assigned weight	Municipality
0.08	Annecy
0.01	Arras
0.00	Avignon
0.00	Valenciennes
0.00	Colmar
0.00	Calais
0.21	Douai
0.00	Limoges
0.18	Lorient
0.00	La Rochelle
0.01	Boulogne-sur-Mer
0.00	Vannes
0.00	Saint-Brieuc
0.14	Troyes
0.00	Martigues
0.00	Valence
0.00	Brest
0.03	Bayonne
0.00	Pau
0.00	Toulon
0.33	Lens
0.00	Perpignan

80 kilometers west of Dunkerque- now receives a very slight weight of .001. The ability of both models to reasonably match Dunkerque's pre-treatment outcome trend and covariate means, while building on largely similar donot-combinations, indicates a certain stability of the underlying causal structure between partial/full implementation of FFPT and commuting outcomes, thereby adding to the validity of results (Ahmed, 2021); to this end, it also presents an encouraging, but initial, argument for the model's insensitivity to small changes of its parameters.

Thus, I turn to the analysis of the estimated treatment effect of full FFPT-implementation. Since the policy was implemented together with the revamped and extended Bus service system -which the model cannot control for-, a clear treatment effect attributable exclusively to full-FFPT cannot be

interpreted. Further, figures 8 and 9 make apparent that a clear distinction between this treatment effect and the one exerted by the preceding partial FFPT-policy is difficult, as synthetic and real-world Dunkerque trends begin significantly diverging after 2016, and thus pre- full FFPT implementation. Taking only the time post-2018 into account yields an average treatment effect of 1.19% (or 1.59% when also considering September-December 2018), but since the trends already diverged previously this cannot be attributed to full-FFPT implementation, since the SCM assumption of equal pre-trends does not hold. Instead, it may be reasonable to assume that the only very slight increase in Bus-commuters between synthetic and real-world Dunkerque visible between 2018 and 19 in figure 9 may represent one -or both- of the following: 1) That the introduction of full FFPT had a stabilizing effect on the commuting transport split falling on Buses.

Figure 9: *Trend gaps Dunkerque vs. Synthetic Dunkerque – 2018 model*



2) That commuters working during the week -as previously their counterparts working on weekends/holidays only adapt their transport behavior with a slight lag. Interpretation 2) seems intuitive since figure 9 again depicts a slight initial drop (-0.12%) of Bus-usage immediately after partial FFPT implementation, before modeling a significant uptick of 1.53% between 2017-18. Additionally, since the new policy enables all commuters to take the Bus - instead of only those working on commonly free days- it is possible that a certain “saturation” regarding the commuters benefiting by partial FFPT implementation has been reached, and that their “normally” working counterparts first need to adapt to the full FFPT-policy for it to take significant impact. Finally, the yearly gaps -and thus estimated treatment effects- are quite similar in size between both models (apart from 2015), further adding to the robustness of the treatment effect assignable to the initial, partial implementation of partial FFPT. Under the assumption that partial and full removal of bus-fares had two only partially overlapping target audiences in terms of commuting behavior -people working “normal” days and people (also) working on weekends- one could assign the 2015 to 2019 treatment effect to the initial policy, thereby calculating an average yearly treatment effect of 0.54% (also 0.54% when only considering September – December 2015 in the calculation). Despite the discussed indications, this treatment effect can however also not “cleanly” be assigned to only partial-FFPT introduction, as the stabilization between 2018 and 19 -compared to the slight decrease between

2015 and 16, may for example indicate that full-FFPT, and/or the revamped bus system, had a slightly more immediate effect than its predecessor.

In sum, the 2015 and 2018 results thus indicate a good ability of the SCMs to construct valid counterfactuals and indicate a stable causal effect of (partial) FFPT introduction on commuting behavior. To provide more than indications, however, the models must prove robust across different tests concerning both in-time and in-space stability. The next section thus seeks to evaluate the validity of the results through conducting such tests, and modeling SCMs on other commuting transport split outcomes.

5.2 Robustness tests

5.2.1 Placebo tests

To evaluate the validity of the discussed results, a series of in-space and in-time placebo tests is conducted. In-space placebo tests here refer to checking how the model reacts to exchanging Dunkerque for a placebo donor-municipality which did not introduce (partial) FFPT in the covered timeframe (Ahmed, 2021; Cunningham, 2021). Figures 10 and 11 plot the gaps between the respective real-world municipality and their synthetic counterparts (as in figures 7 and 9) created by iteratively assigning the treatment across all donor municipalities (in gray) next to the gaps between synthetic and real Dunkerque (in Black).¹³ To facilitate the interpretability of the figures, extreme cases -that is, those with an excessive pre-treatment MSPE, and thus divergence, between synthetic and real-world plot- are not depicted.

¹³ This is noted in the text as while the *plot_placebos* function of *synth* automatically creates a (non-changeable) legend, it kept displaying the legend falsely, with Dunkerque being “grey” and the placebos “black”.

Figure 10: *In-space placebos - 2015 model*

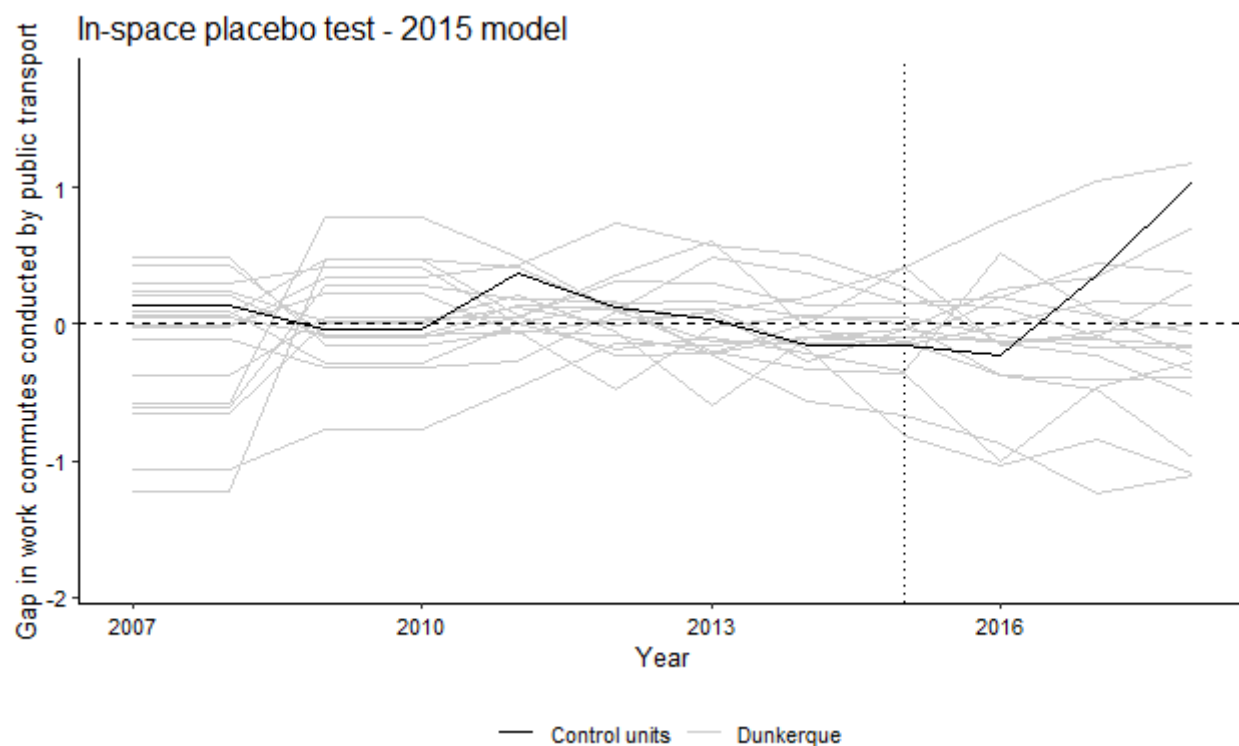
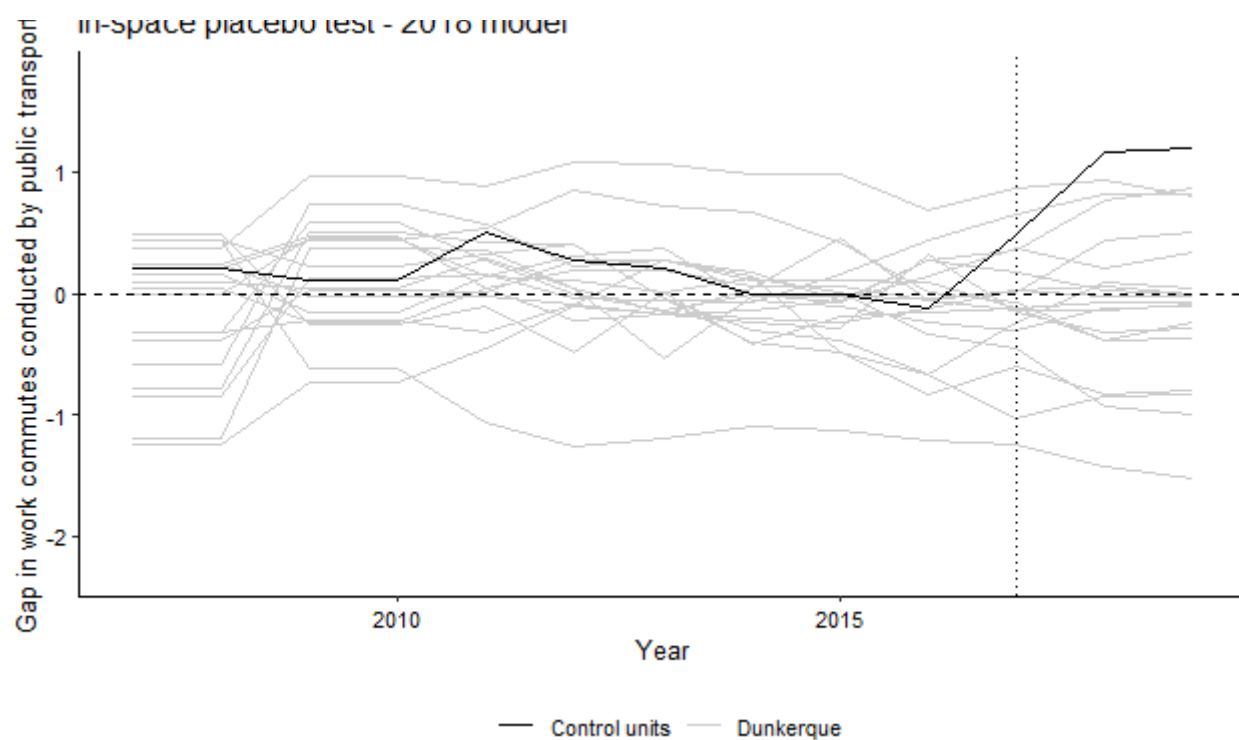


Figure 11: *In-space placebo test - 2018 model*



If the discussed findings indeed showcase the treatment effects of (partial) FFPT-implementation, then the plot of Dunkerque should display the largest, or among the largest, gap between synthetic and real-world case in the post-treatment period(s), compared to other municipalities where the synthetic control also reasonably tracks the pre-treatment outcome (Andersson, 2019; Cunningham, 2021). If not, then the post-treatment divergence of Dunkerque may not display the treatment effect but could instead be caused by unknown factors biasing the result, or simply occur at random (*Ibid.*). This however does not seem to be the case in figure 8 and especially figure 9, with Dunkerque's post-treatment gaps clearly among the highest compared to the placebo plots. Indeed, the only plots with similar post-treatment gaps also feature larger gaps in the pre-treatment period, thereby indicating that they would not satisfy the SCSM's underlying assumption of close to identical pre-treatment trends to measure the post-treatment effect.

This assumption can also be used for implementing a closely related robustness test: Since SCM builds on establishing similar pre-treatment trends -therefore minimizing the MSPE in this period- a valid model should display a higher MSPE in the post-treatment than in the pre-treatment phase. Thus, calculating the ratio between Post- and Pre-treatment MSPE for Dunkerque and the placebos can provide an indication of to what extent each model satisfies this assumption, and -if the Dunkerque models indeed capture the treatment effect of (partial) FFPT implementation- yield comparatively high results for them (Abadie et al., 2010, 2015; Cunningham, 2021). Figures 12 and 13 display the results of calculating these ratios for the 2015 and 2018 model. As is visible, Dunkerque features the highest ratio by some distance in both cases: For the 2015 model depicted in figure 12, Dunkerque's post-treatment MSPE is ~15 times higher than its pre-treatment MSPE, thereby roughly double that of second-placed Perpignan, and three times higher than that of all but four placebos. The picture is even clearer for the 2018 model, where Dunkerque's Post/Pre-treatment MSPE ratio of ~21 is at least twice -and mostly >4 times- as high as that of the placebos. In both cases, the chance to randomly obtain an equally high ratio -and thereby measure a treatment effect of comparable size- is thus $1/23 = 0.043$ (Abadie et al., 2015; Andersson, 2019). In other words, the treatment effect measured by both models is statistically significant at the 95% confidence interval, which however should not be overinterpreted in the context of causal inference via SCM.¹⁴

¹⁴ Note that figures 12 and 13 include all donor-municipalities, instead of excluding those whose pre-treatment MSPE was more than 20 times higher than that of Dunkerque (as done for figures 8 and 9). Existing literature provides no clear consensus whether such extreme cases should be excluded or not (see e.g. Andersson 2019; Ahmed 2021), so I decided to include them as they do not infringe upon interpretability. For the sake of

Figure 13: *Post/pre MSPE ratio - 2015 model*

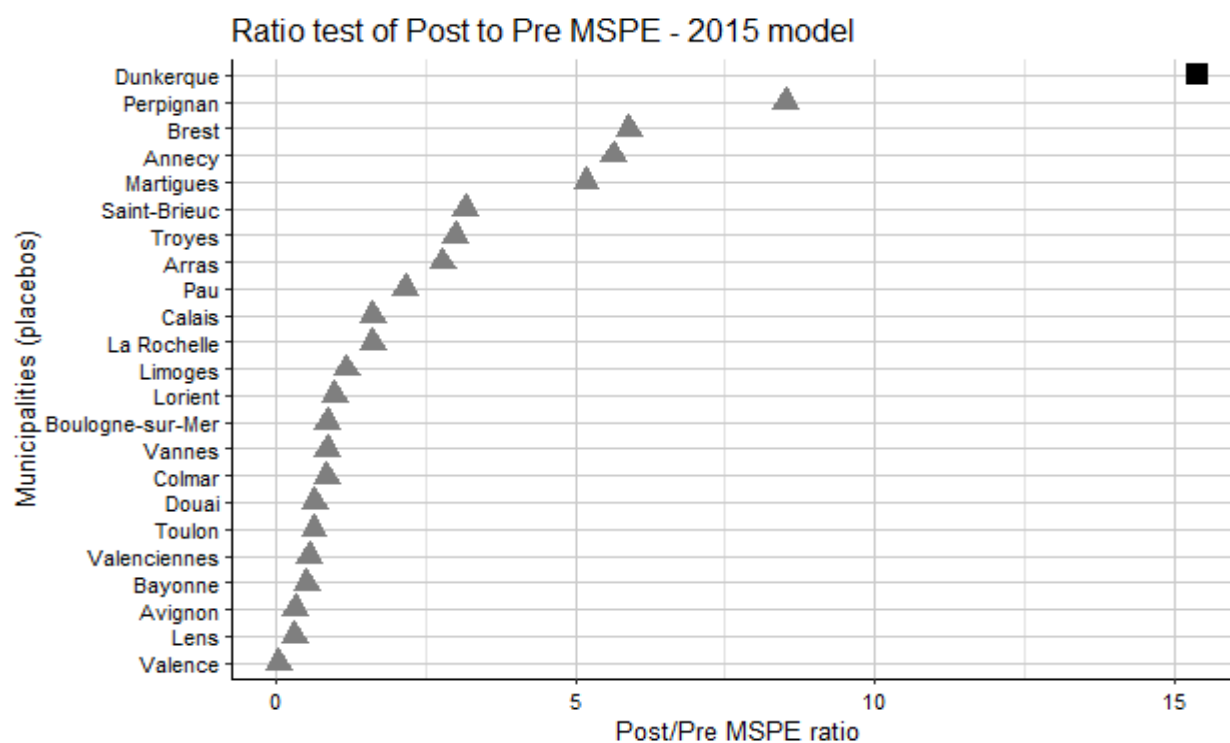
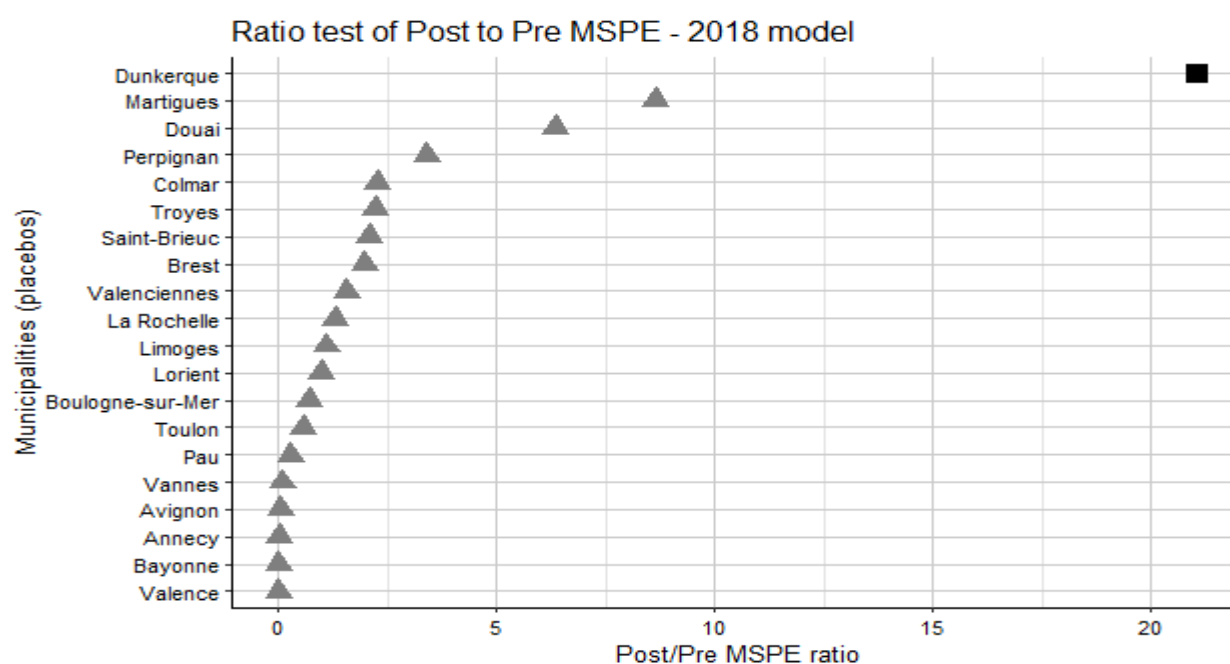


Figure 12: *Post/pre MSPE ratio - 2018 model*

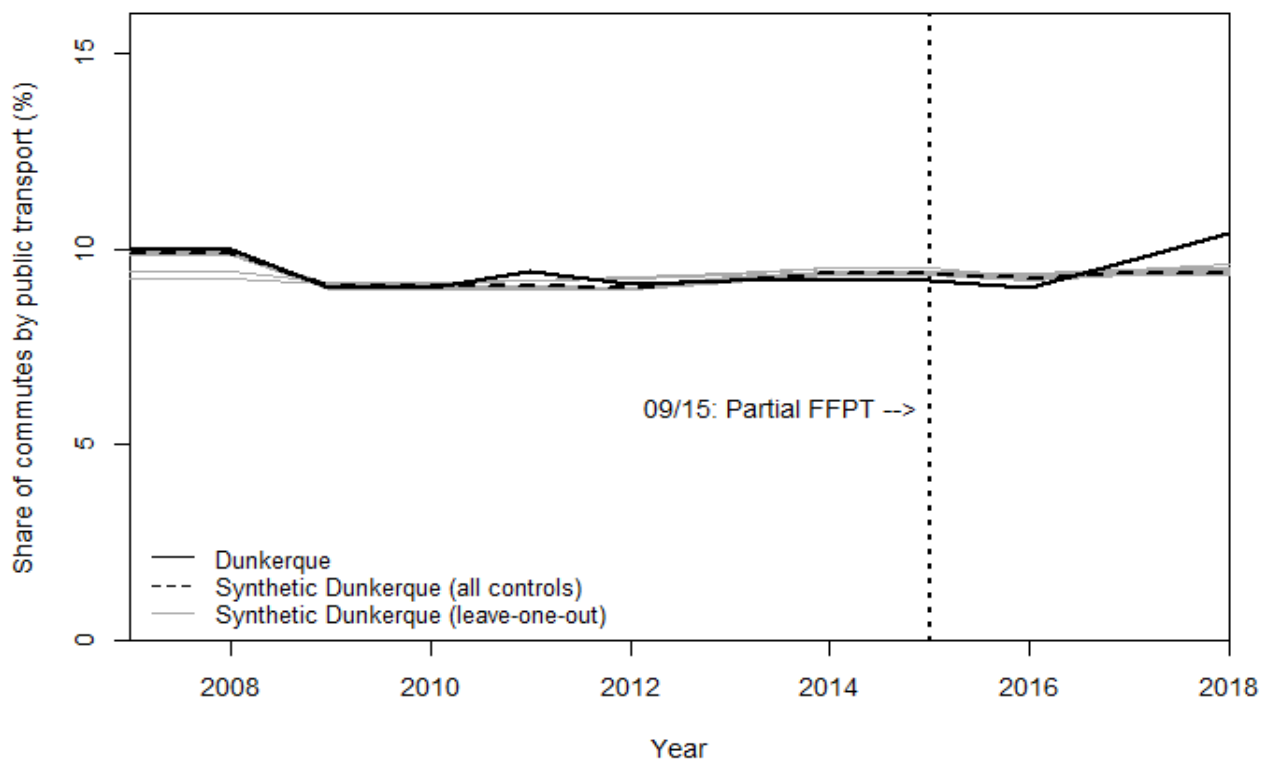


transparency, however, excluding them yields a p-value of 0.055 (1/18) for the 2015 model, and 0.05 (1/20) for the 2018 model. Under these conditions, the 2015 model thus loses its statistical significance due to insufficient sample size.

5.1.2 Leave-one-out test

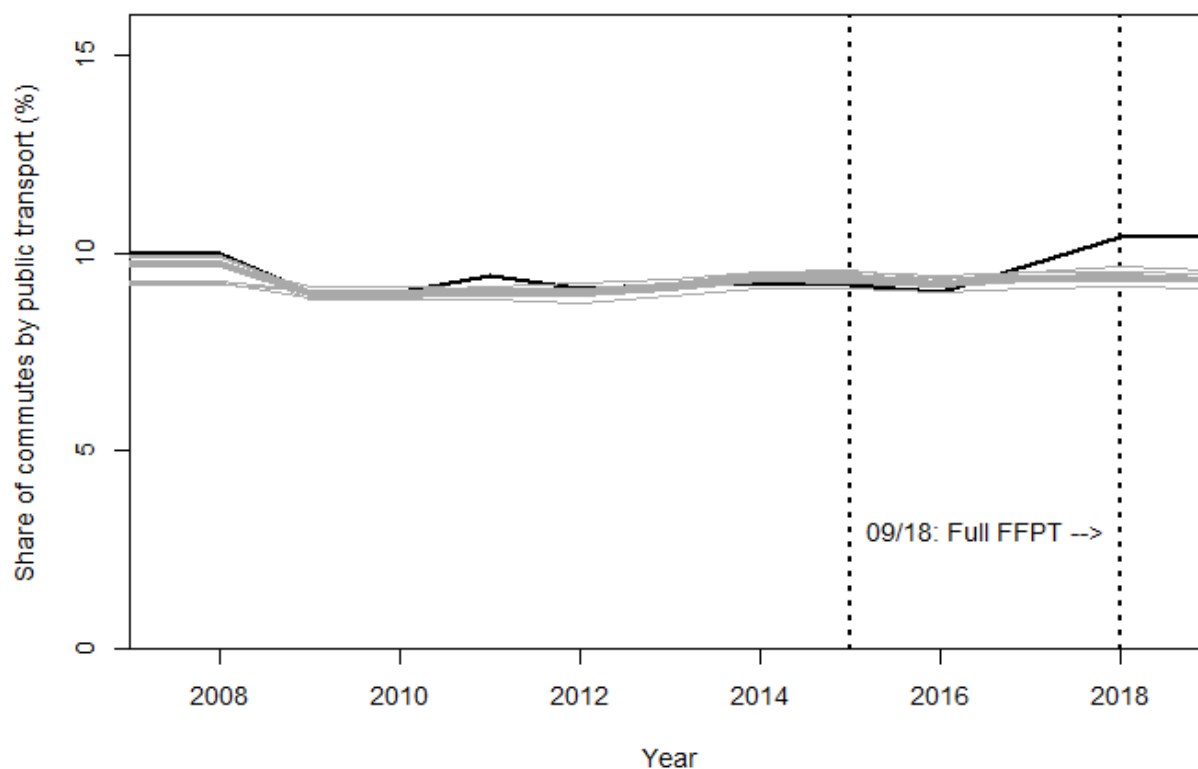
Next, a *Leave-One-Out* robustness test is conducted; as the name suggests, this test iteratively removes one of the 22 donor municipalities before plotting the synthetic control, thereby providing insight into whether the model is sensitive to the removal of (a) specific donor(s). While this is especially relevant concerning the removal of the municipalities which received the most weight in the W matrices, the placebos for all municipalities -even the ones not receiving weights in the models- are computed.¹⁵ If our models are robust, the removal of any control municipality should not exceedingly influence the pre-treatment fit to real-world Dunkerque and/or the estimated treatment effect.

Figure 14: *Leave-one-out distribution of the 2015 SCM*



¹⁵ This differs from the approach e.g. used by Abadie et. al. (2015), which only plot the placebo for those donors receiving a weight of at least .001. To ensure that the model is truly not sensitive to any changes of the donor pool, I however decided to conduct the test across all municipalities.

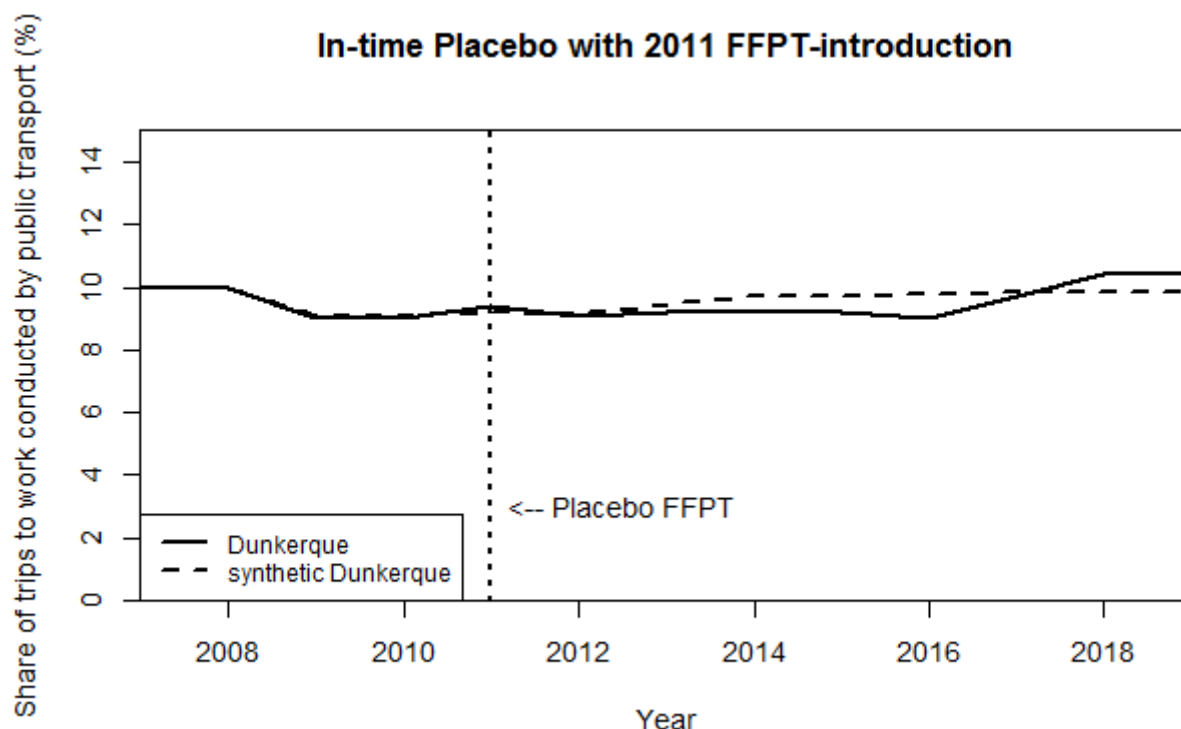
Figure 15: *Leave-one-out distribution of the 2018 SCM*



As figures 14 and 15 show, neither model seems particularly sensitive to the exclusion of any specific municipality from the donor pool; while the ability to track the pre-treatment trend varies between cases, especially for the 2007 – 2009 period, the overall pre-treatment and post-treatment trajectory does not vary very strongly for any placebo. That being said, the observable differences are slightly larger in case of the 2018 model (Figure 15), thereby rendering this model -and the estimated treatment effect- slightly more sensitive.

Finally, an *in-time* placebo test is conducted, which refers to reassigning the treatment to a period before actual (partial) FFPT implementation; should this model estimate a treatment effect of similar magnitude to the SCMs for the 2015 and 2018 treatments, it may indicate that their post-treatment divergence does not necessarily capture a treatment effect, but is rather caused by a lack of predictive power of the model(s) (Abadie et al., 2015). The fact that relatively few pre-treatment observations are available may somewhat complicate the implementation of this test, as it limits the options of when to assign the placebo-treatment: I choose 2011, in the middle of the pre-treatment timeframe.

Figure 16: *In-time Placebo with FFPT introduced in 2011*



As figure 16 indicates, this test is at best partially passed. The post-treatment trajectory runs in a different direction than with the actual treatment models, thereby estimating a slightly delayed negative treatment effect. While thus not estimating a treatment effect of similar magnitude going in the same direction, this result does indicate that the SCM may lack predictive power in the post-treatment period. While the previous constancy in treatment effects between the 2015 and 2018 models may be attributable to the later building on “pre-treatment” data featuring a (soft) treatment, figure 14 indicates that the model(s) may be time sensitive. I say may as the placebo builds on very few pre-treatment periods, which may serve as an alternative explanation for its lack of predictive power; nevertheless, this result cautions against a too confident interpretation of the previous post-treatment divergence between synthetic and real-world Dunkerque as capturing a real treatment effect. Thus, a final robustness test estimating the impact of (partial) FFPT implementation on other outcome(s) of the commuting transport split is conducted.

5.3 Modelling other outcomes of the modal transport split

Apart from the envisioned increase in public transportation usage, many proponents of FFPT-schemes also cite their potential of alleviating environmental and/or general societal concerns -such as air/ noise pollution or congestion- associated with the dominance of cars in the modal transport split (David et al., 2018). Indeed, such concerns also formed part of the reasoning behind introducing free public transportation in Dunkerque (Dairaine, 2019). To contribute to such goals, (partial) FFPT in Dunkerque must not only result in more people using the bus, but a significant portion of new users should also previously have primarily used their car; indeed, the discussed qualitative findings indicate that such a process may be unfolding (Huré et al., 2019).

This goal provides this study with an additional avenue through which to test the robustness of its results. Since the outcome of people commuting by public transport is given as a percentage of the overall commuting split, any positive change in it must be reciprocated by a negative change in one or more of the commuting splits falling on cars, bicycles, or pedestrians. Thus, applying the same model(s) utilized above to other commuting outcomes and estimating a negative treatment effect of similar magnitude would provide an argument for the model accurately representing commuting outcomes in Dunkerque, and thereby for the robustness of their findings. Under the assumption that cars should represent the closest alternative to Buses for the average commuter – given that commutes are often too long for non-motorized transport (Rasca & Saeed, 2022) – they receive special attention.

Figure 17: *Commuting by car - Dunkerque vs. Synthetic Dunkerque 2015 model*

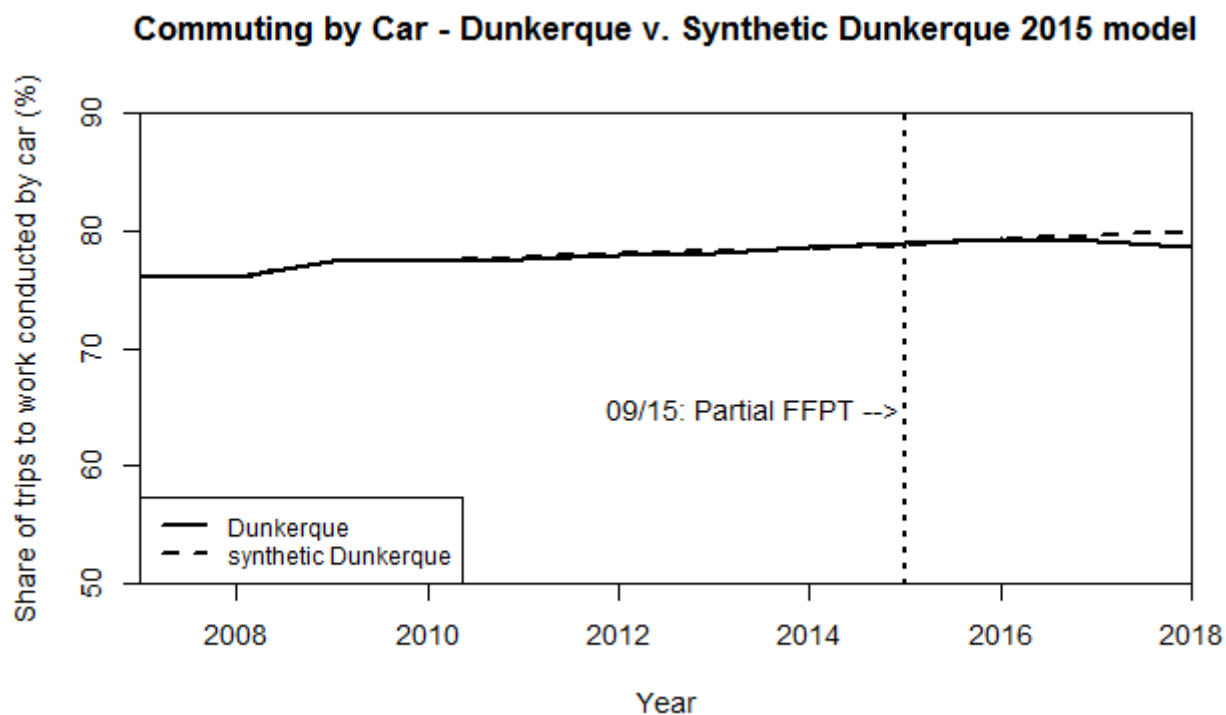
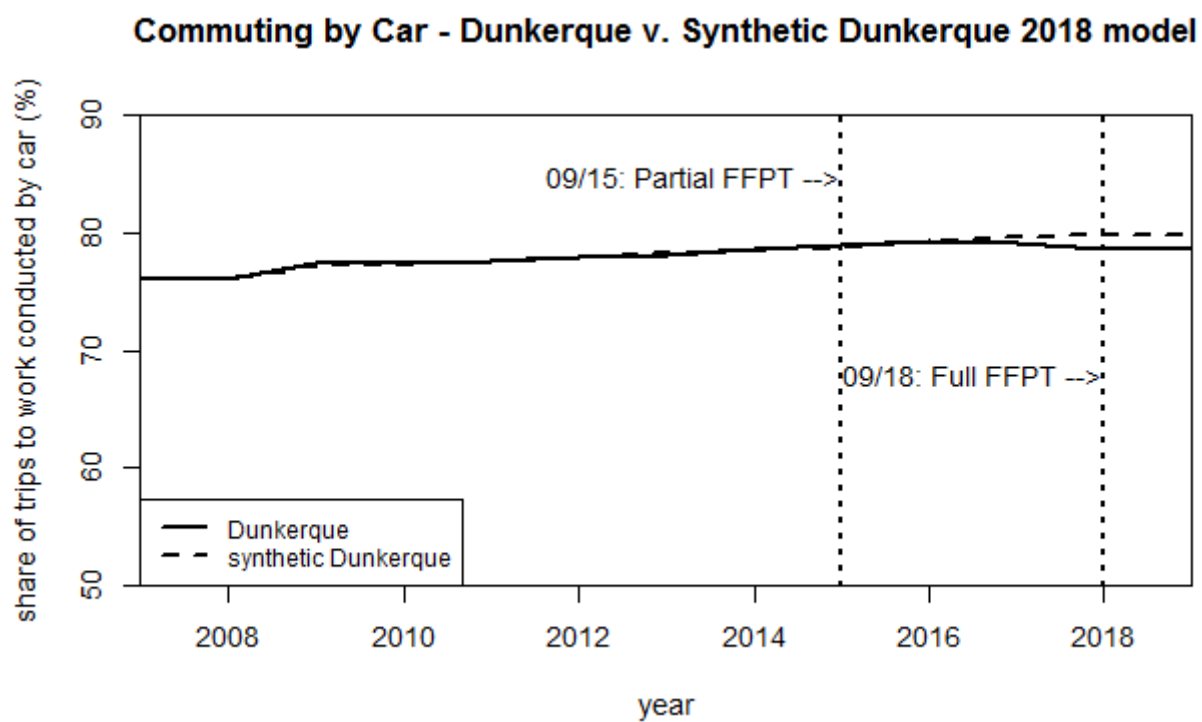


Figure 18: *Commuting by car - Dunkerque vs. Synthetic Dunkerque 2018 model*



Figures 17 and 18 showcase the results of estimating the effect of (partial) FFPT introduction on the share of individual commuting by car. As visible, both synthetic Dunkerque's produce a practically identical pre-treatment trend to real-world Dunkerque; both also achieve reasonable (2015 model) to very good balance across the most heavily weighted predictors in the pre-treatment period (see Annex III).¹⁶ This good performance results in high Post/Pre MSPE ratios (~28 for 2015 and ~47 for 2018 model (see Annex III)). However the 2015 model has Valenciennes achieving a Post/PreMSPE ratio almost twice as high as Dunkerque, thereby giving it a non-statistically significant p-value of 0,086. In 2018, Dunkerque achieves the highest Post/Pre MSPE ratio, and thus statistical significance (0,043). In sum, one could argue that the utilized models perform (even) more capable of modelling pre-treatment outcomes of car-commuters than those of public transport. Thus, one can interpret their post-treatment gaps as capturing the treatment effect(s) of (partial) FFPT introduction with some confidence.

Doing so then provides an argument for the robustness of the results obtained by modeling commuting behavior by public transport. Both figures 17 and 18 estimate a negative treatment effect on commuting by car which begins after 2016 – thereby mirroring their public transport-counterparts in the timing of the estimated treatment effect, which goes in the opposite direction. Specifically, the 2015 model estimates an average annual treatment effect of -0.38%, or -0.31% when only taking September – December 2015 and January – August 2018 into account. This exceeds the annual treatment effect estimated by the 2015 Bus model (annual rise of 0.25% or 0.21%), but nevertheless may indicate a correlation between both figures. The 2018 model estimates a treatment effect of -1.64% when assuming a clear cutoff and immediate effectiveness of full FFPT-implementation in 2018 (vs. an 1.59% predicted increase of bus users in the same timeframe). Both policies combined are estimated to result in an annual average decline of -0.53% (- 0.55% when only taking September – December 2015 into account) of commuters driving to work by car, thereby accounting for the projected increase of 0.54% (for both calculations) of Bus users quasi one-to-one.

Figures 19 and 20 finally estimate the effect of (partial) FFPT implementation on people walking and cycling to work across the whole available timeframe. Figure 20 tracks the pre-treatment outcomes of cyclists quite closely, thereby lending credence to the notion that the lack of an estimated treatment effect may actually account for their variation in overall post-

¹⁶ In the interest of readability and to not overcrowd this section with further figures and tables, the covariate balance and weight tables, as well as the gaps plots and in-space placebo tests are provided under Annex III.

treatment commuting split. The same can not be said for figure 19, where the SCM fails to track the pre-treatment outcome of pedestrians. The slight decrease of individuals walking to work experienced in Dunkerque between 2016 and 17 may however account for the slight discrepancy between Car and Bus commuting outcomes in the 2015 models discussed above.

Whether the closeness of particularly the 2018 estimates indicate that the estimated bus and car outcomes causally correspond with each other -that is, whether they are attributable too the same source in form of the implementation of (partial) FFPT – cannot be interpreted from this section alone. Nevertheless, they provide a strong indication that at least in Dunkerque, both forms of transportation are the closest substitutes for each other for at least some workers; perhaps particularly for those working on weekends, as the partial FFPT policy seems to account for the majority of the effect in both outcomes, and may contribute to its overall modest size. In any event, the combined strong performance across all four models and both outcomes, together with the closeness and intuitive opposed directionality of results, provides a strong argument for the robustness of their results.

Figure 19: *Walking to work - Dunkerque vs. Synthetic Dunkerque*

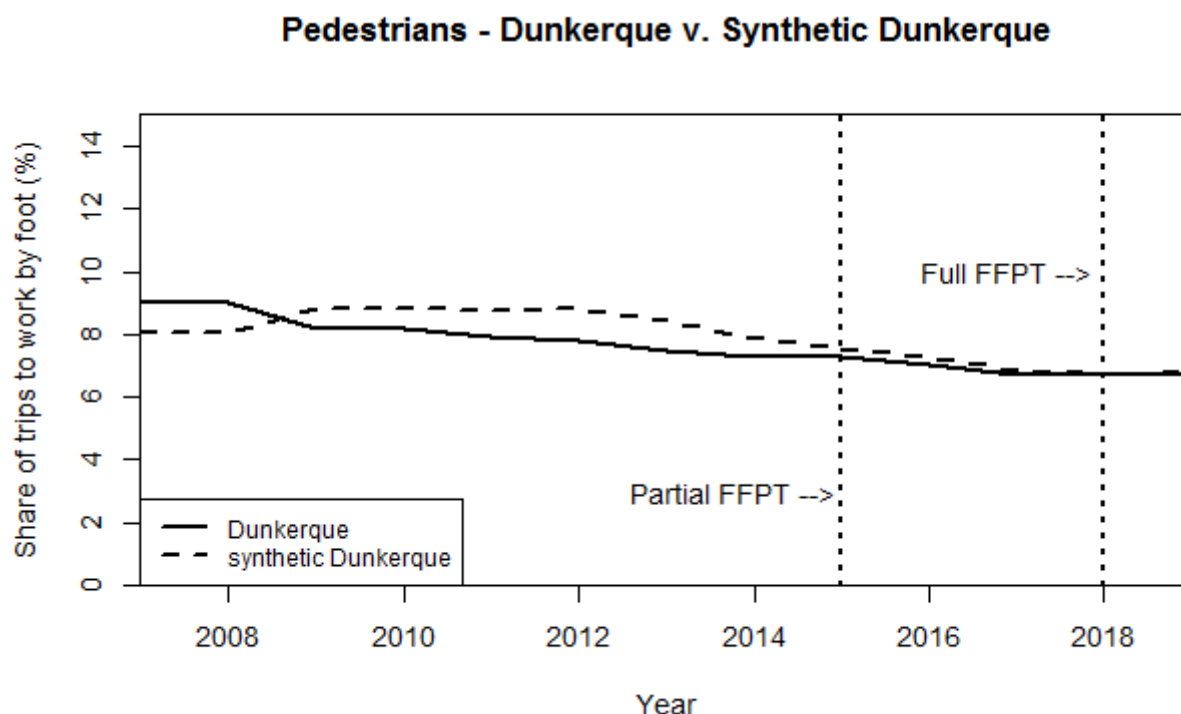
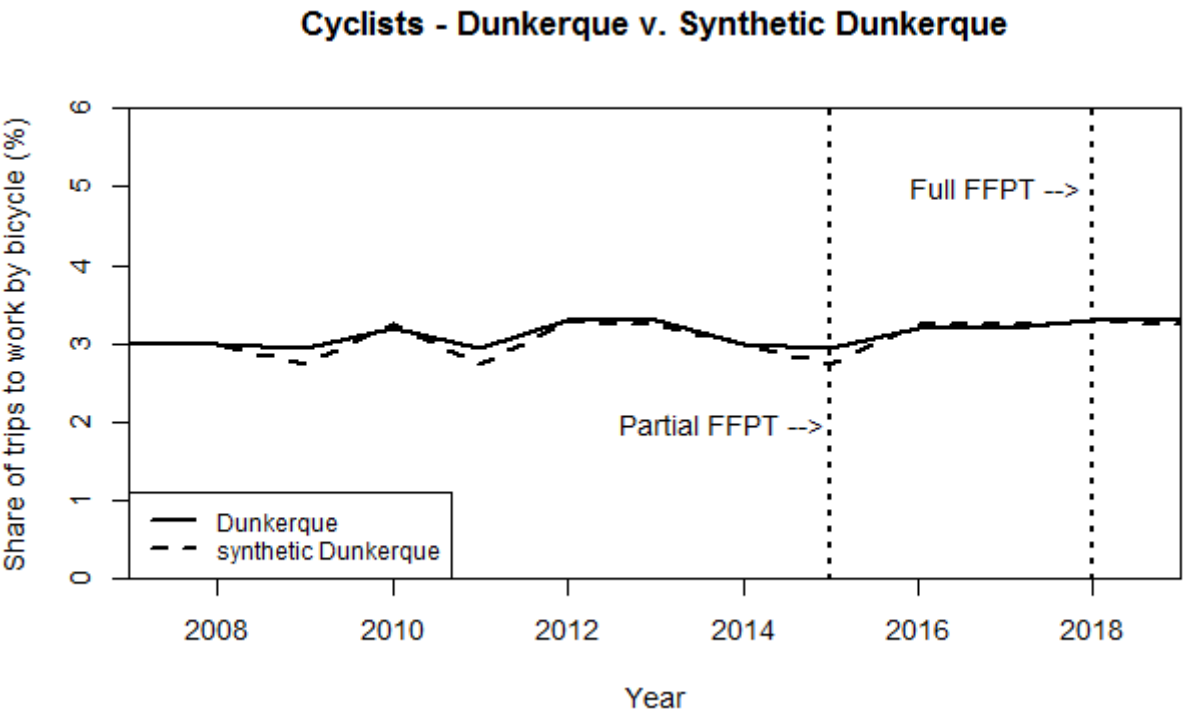


Figure 20: *Cycling to work - Dunkerque vs. Synthetic Dunkerque*



6. Discussion & Limitations

Taken together, the presented models provide a strong indication that the observable increase individuals commuting by Bus in Dunkerque is indeed largely attributable to the removal of Bus fares. Specifically, the robustness of results in scope and time across models seeking to estimate the impact of partial (2015) and full (2018) FFPT implementation on both public and private transportation outcomes indicates that within the available time frame, the discernable treatment effect is likely to have mainly been caused by the former policy. Given that the introduction of general FFPT in 2018 coincided with an increase in service supply and availability through the inauguration of the revamped Bus system, this may also render the estimates “cleaner” in the sense of being more convincingly attributable to FFPT specifically.

Understanding the visible effect as having been mainly caused by partial FFPT may then also provide an intuitive -not causal- context for the overall modest annual treatment effect 0.54%, as the pool of work-commuters is likely to be smaller on weekends and -especially- public holidays. In this regard, it is also important to contextualize the estimated treatment effect via the factors potentially beneficial to or subtracting from the effectiveness of FFPT present in Dunkerque. As tables 2 and 4 showcase, Dunkerque displayed lower average levels of median disposable income, car-availability and average commuter numbers compared to the pool of similar-sized donor municipalities. Given that existing literature draws a substantial negative (but non-causal) linkage between especially the first two predictors and PT-demand (see e.g. Hidalgo & Huizenga, 2013; Paulley et al., 2006) -which is further corroborated through the high assigned weights across different SCMs-, one could argue that Dunkerque’s partial FFPT scheme should have fallen on fertile ground, and thus achieved a higher affect. Conversely, however, the fact that previous causal forays into the effects of FFPT/fare-price subsidies (Bull et al., 2021; Gohl & Schrauth, 2022) found their positive treatment estimates to be conditioned on and/or heavily linked to PT-supply factors would suggest that implementing partial FFPT within Dunkerque’s then very limited Bus-network should heavily impede the policies’ ability to attract new commuters.¹⁷ Interpreting whether these factors cancel each other out or one takes precedence in the context of Dunkerque is hard to do, especially given this studies’ limited ability to observe post-2018 outcomes including an increase in PT-supply. While I am inclined

¹⁷ Indeed, the introduction of free 20-minute parking as part of the *projet Phoenix* could also work against FFPT-effectiveness as a measure reducing the cost of car-usage (Cui et al., 2021; Margaryan, 2021). However, given that commuters likely require longer parking times it seems implausible that this would effect their specific transport-decisions, and should thus not effect the treatment effect in the context of this study.

to interpret the estimated treatment effect of partial FFPT as not-insubstantial given the specific outcome under study and the inadequate nature of Dunkerque's pre-2018 PT-network, this view could be subject to debate.

The robustness of results particularly across space-placebos alleviates concerns regarding the un- or insufficient availability of predictors commonly associated with modal transport patterns such as average fuel prices or land-use patterns (Chen et al., 2011; Rasca & Saeed, 2022). It appears that a combination of the chosen predictors and donor municipalities can track Dunkerque's pre-treatment commuting outcomes falling on Buses and -perhaps even more- Cars quite well and produce a balanced counterfactual, without being overly sensitive to the exclusion of any single control municipality. Thus, it seems unlikely that any variance of a non-considered and/or unobservable factor is heavily biasing the results. As briefly mentioned above, the commonly most weighted predictors of available cars per 1000 inhabitants, median disposable income and average total number of commuters are in line with previous findings regarding their importance for the modal transport split and seem to confirm that cars continue to be the closest substitute for public transport (Hidalgo & Huizenga, 2013). In sum, it appears that the implemented synthetic controls are quite capable of modelling commuting outcomes in Dunkerque.

Nevertheless, the models cannot dispel all doubts regarding the robustness of their results. The apparent sensitivity to reassigning the treatment period via an in-time placebo showcases that the available data may not cover sufficient time periods to result in models with very strong predictive power. At the very least, the lack of pre-treatment observations precludes commonly utilized techniques to verify the ability of synthetic Dunkerque to track its real-world counterpart -such as creating training and validation subsets (Abadie et al., 2010). Thus, the ability to verify the central assumption of the synthetic control method -namely that closely matched pre-treatment outcomes result in a valid non-treated counterfactual in the post-treatment period- is diminished. Further, the limited availability of post-full FFPT outcomes sadly negates the ability to estimate its effect after the possible adoption lag already present in its predecessor.

This is especially unfortunate given that the simultaneous abolition of transport fares and increase in service-supply would also constitute a prime opportunity to study the real-world (causal) effectiveness of trying to induce a Mohring-effect (Mohring, 1972). Specifically, the (aforementioned) almost conditional role PT-supply factors seem to play in the success of FFPT-policies found in previous causal studies give reason to that the scope of the here

estimated treatment effect may significantly increase in the foreseeable future. Thus, while the onset COVID-19 pandemic in early 2020 would surely present considerable (methodological) challenges for estimating a “clean” causal treatment effect during this period, the coming post-pandemic years should thus continue Dunkerque’s status as real-world “laboratory” for causally studying the effects of FFPT introduction.

Finally, the fact that two-treatment outcomes (2008 and 2009) of Dunkerque had to be imputed renders its status of “real-world” case as only partially true, as it instead contains some “synthetic” elements itself. Although most imputations concerned observations with some temporal distance to the treatment(s), at least some were performed across all municipalities and outcomes/predictors, thereby rendering it impossible to completely negate the possibility of this biasing results in any way. Specifically, median disposable income (featuring ~31% of imputed observations) receiving considerable weight across different models may bias results, although the predictor featuring most imputed values (cost of a 5km taxi ride at ~38%) did not receive substantial weight. Indeed, removing the median disposable income from the predictors inhibits the SCMs ability to track Dunkerque’s pre-treatment trend (for both 2015 and 18) from 2007-10 (see Annex II), although the estimated treatment effect remains largely unaffected. Given the weight placed on the predictor, this is not surprising (especially as removing average taxi fares even improves model performance in terms of tracking Dunkerque’s pre-treatment trend). Nevertheless, model performance thus slightly depends on the inclusion of a predictor with 30% imputed values, thereby calling for further caution in interpreting the results.

7. Conclusion

Does the experience of Dunkerque indicate that removing the monetary costs of travelling via public transportation increases usage? The evidence provided in this study suggests so, thereby causally corroborating the results of the qualitative evaluations and adding mid-sized cities to the list of contexts in which a growing body of (causal and non-causal) literature finds similar results.

Despite limitations imposed by data availability and completeness, the consistency of models estimating a positive treatment effect provides a strong indication that the observable increase of individuals commuting via Bus is indeed attributable to the introduction of FFPT. Indeed, the fact that this effect is likely mostly caused by the initial policy only being effective on mostly work-free days contextualizes the estimated annual increase of 0.54% as arguably not insubstantial, given the reduced pool of policy targets and the fact that this effect transpired in the context of a Bus system generally deemed inadequate in terms of availability and scope. Moreover, in contrast to most existing literature, there is evidence to suggest that the policy also found the “right” targets, in that the scope of the estimated annual increase in PT-commuters is essentially matched by that of the estimated decrease in drivers. Given the persistent dominance of cars over other modes of transportation in Europe and many parts of the world, as well as the “second-rate” nature of FFPT as a policy-option to change this outcome commonly diagnosed in the literature, this finding presents perhaps the strongest argument for the apparent success of Dunkerque’s (partial) FFPT policy.

Thus, this study provides a strong indication that Dunkerque’s (partial) FFPT policy heavily contributed to achieving the stated goal of 10% of trips falling on PT, albeit in the commuting transport split, which started off at a comparatively higher level. Second, there is a strong indication that this effect was achieved through inducing a modal substitution away from cars towards Buses. However, the fact that the employed models do not pass all robustness tests advises against an all-to confident interpretation of these results. In the pursuit of addressing the causal attribution problem, all quasi-experimental methods inherently rely on the formulation of strong assumptions; any infringement on their verifiability thus provides cause to exercise additional caution in formulating claims about the causality of uncovered effects. Rather than as a definitive answer about the specific effect of implementing (partial) FFPT in a medium-sized city with an ailing Bus network, it thus seems pertinent to interpret the findings of this paper as a strong argument for the potential effectiveness of the policy, but only as a

substantial, rather than definitive, foray into its causality. To this end, it provides a stronger argument for the systematic causal evaluation of FFPT (and fare-price subsidizing) regimes emerging in other mid-sized cities to allow for a further contextualization of results.

At a time when both the number and the size of cities -or even countries- considering the abolition and/or heavy subsidization of public transport fares is rapidly increasing, the need for causal assessments of their effectiveness is expanding accordingly. This study contributes to the discussion by adding to the evidence that the intuition behind FFPT may well translate into reality, even in a context characterized by a lack of adequate PT-supply. Moreover, it suggests that the potential of such policies to render PT services as a viable substitute for cars may currently be underestimated. However, further academic study and policy deliberation is required to relegate FFPT from its current “second-best” position as response to unsustainable transport patterns. That with Calais (December 2019) and Douai (January 2022) two cities similar to Dunkerque decided to follow its example by introducing their own FFPT-schemes may thus be welcomed: Both as a commitment to more accessible and sustainable transport, and as new laboratories through which to causally evaluate the findings of this study, and the concept of FFPT as a whole.

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Annex I: Data imputation and overview of missing observations per variable

1.1 Imputation

The imputation of missing values was performed via the linear interpolation function provided through the `imputeTS` package available in R (Moritz & Gatscha 2022). Assuming a linear relationship between different observed values of the same variable, linear interpolation imputes missing values through calculating a mean based on the last available observation before (A) the missing value (N), and the first available observation after the missing value (B) (Moritz & Gatscha 2022, Mohamed Noor et. al. 2014); thus, the linear imputation function essentially applies the following function to each missing observation for each variable in the dataset (Ibid.):

$$f(Nvalue) = Bvalue + (Avalue - Bvalue) * (Nyear - Byear) / (Ayear - Byear)$$

Imagined graphically, the value here denotes the observed value of A/B on the y-scale in a time-plot of a given variable, whereas year denotes the corresponding value on the x-scale. To not cross-contaminate imputed values, the imputation was further performed individually for each municipality in the dataset (see Annex B for the utilized R command?). Table 6 showcases an example of imputed values for the modal transport split of commuting to work falling on public transportation (`modal_PT`) in Dunkerque. As visible, imputation resulted in the observations of 2008 and 2009 receiving the same value as 2007 and 2010, respectively. Under the assumption that `modal_PT` develops in a linear fashion and 2008 and 2009 did not see the occurrence of a sudden event and/or shock heavily influencing public transportation usage other than the declining trend inferable from the 2007 and 2010 values, the imputed values seem reasonable. Furthermore, it is important to note that imputation took place relatively long before the introduction of partial (2015) and full (2018) FFPT, meaning that the later analysis of post-treatment outcomes is not based on imputed values.

Table 6: Eurostat and imputed datasets Dunkerque

Year	Eurostat Dataset	Imputed Dataset
2007	10.0	10.0
2008	NA	10.0
2009	NA	9.0
2010	9.0	9.0
2011	9.4	9.4
2012	9.1	9.1
2013	9.2	9.2
2014	9.2	9.2
2015	9.2	9.2
2016	9.0	9.0
2017	9.7	9.7
2018	10.4	10.4
2019	10.4	10.4

Table 7: Percentage of missing observations per variable¹⁸

Variable	Percentage of NA	Variable	Percentage of NA
<i>length_bicycle_network</i>	1	<i>average_disposable_income</i>	0,393442623
<i>traffic_noise</i>	1	<i>cost_5kmtaxi</i>	0,382903981
<i>cost_monthly_ticket</i>	0,984777518	<i>median_disposable_income</i>	0,317330211
<i>modal_bicycle</i>	0,618266979	<i>modal_car</i>	0,152224824
<i>modal_car_motorcycle</i>	0,618266979	<i>modal_foot</i>	0,152224824
<i>Share.of.journeys.to.work.by.motor.cycle...</i>	0,618266979	<i>modal_PT</i>	0,152224824
<i>households_apartments</i>	0,613583138	<i>cars_registered_total</i>	0,151053864
<i>households_houses</i>	0,613583138	<i>number_commuters_in</i>	0,151053864
<i>students_1000pop</i>	0,613583138	<i>number_commuters_out</i>	0,151053864
<i>econ_activity_rate</i>	0,613583138	<i>population</i>	0,151053864
<i>unemployment_rate</i>	0,613583138	<i>area_living_accomodation</i>	0,151053864
<i>journeytime_km</i>	0,569086651	<i>econ_activity_rate_20_64</i>	0,151053864
<i>journeytime_min</i>	0,569086651	<i>total_traffic_deaths</i>	0,079625293
<i>PM10_concentration</i>	0,530444965	<i>cities</i>	0
<i>NO2_concentration</i>	0,5	<i>time</i>	0

¹⁸ Note that the variables *cars_registered_1000pop* and *traffic_deaths_10000pop* utilized in the analysis were calculated by the author using the *population* and *cars_registered_total/traffic_deaths_total* variables.

Annex II: Robustness – Generating SCMs while excluding certain donors/ predictors

2.1 Generating synthetic Dunkerque without municipalities with trams

Figure 21: Dunkerque vs. synthetic Dunkerque without Brest/Valenciennes - 2015 model

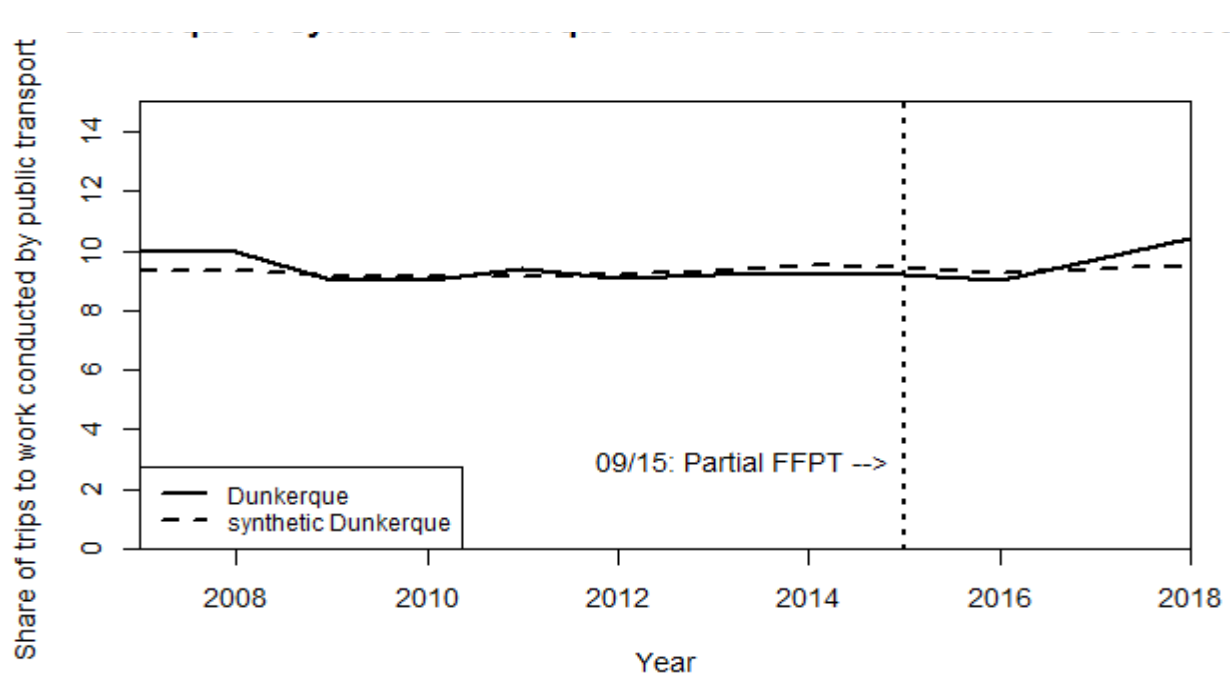
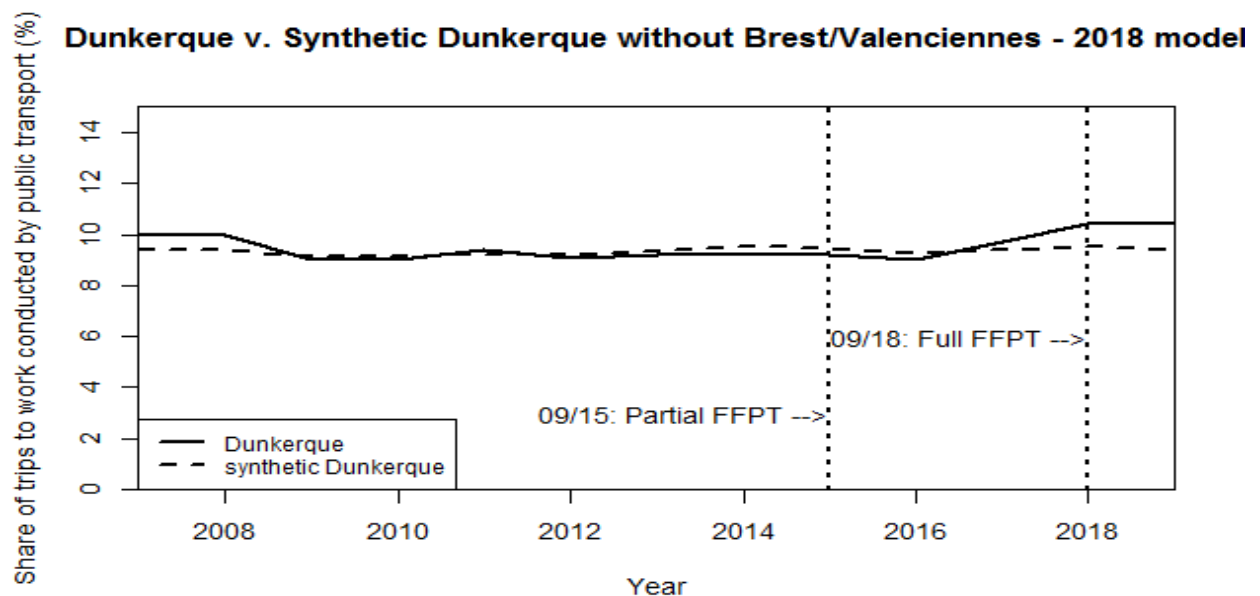


Figure 22: Dunkerque vs. synthetic Dunkerque without Brest/Valenciennes - 2018 model



2.2 Generating Synthetic Dunkerque without the average taxi fares/ median disposable income

Figure 23: Dunkerque vs. synthetic Dunkerque without taxi ride cost - 2015 model

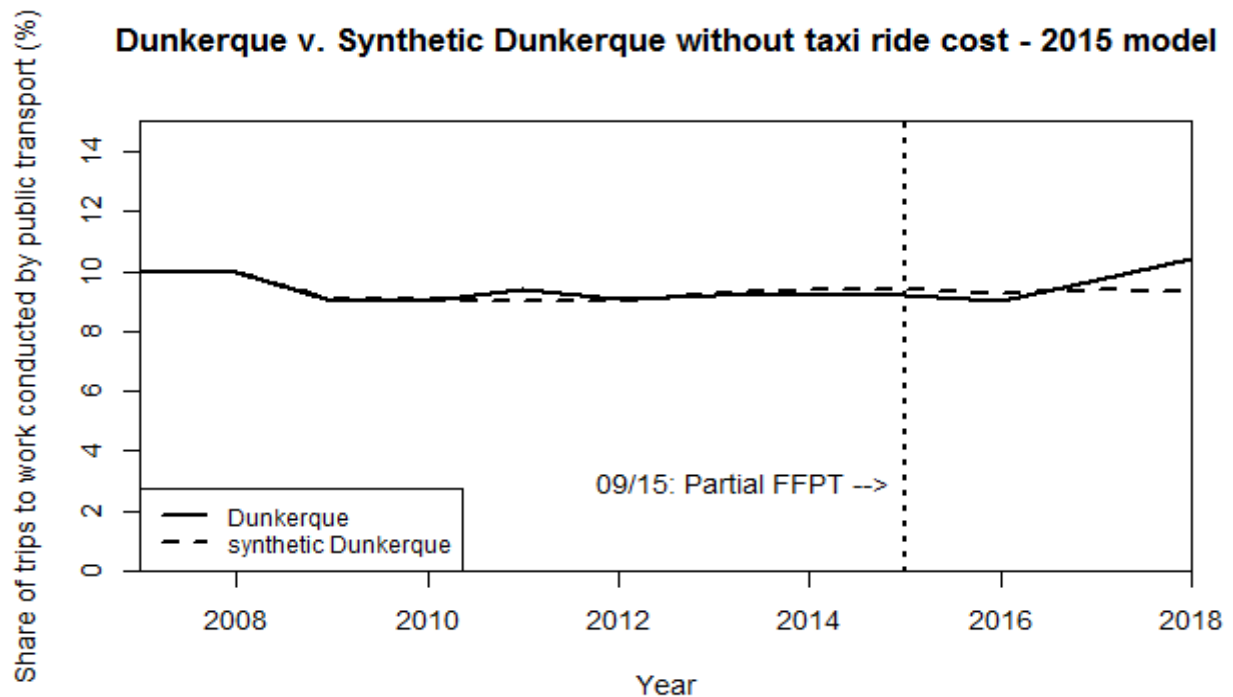


Figure 24: Dunkerque vs. synthetic Dunkerque without taxi ride cost - 2018 model

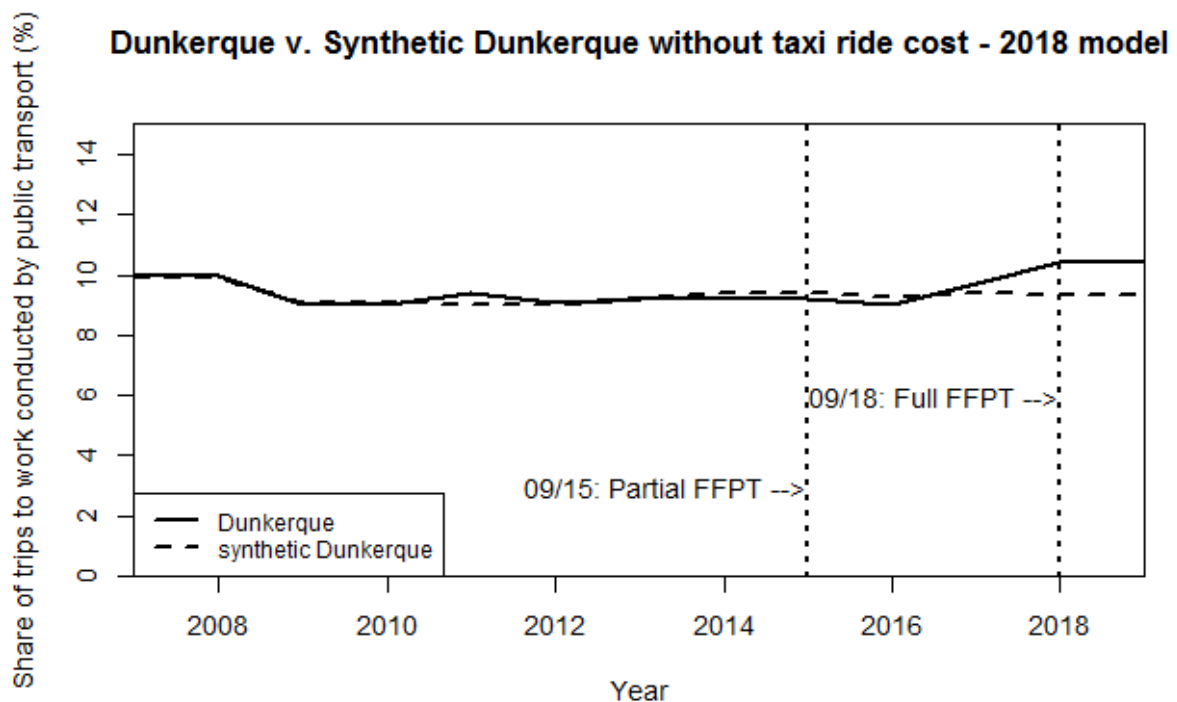


Figure 25: Dunkerque vs. synthetic Dunkerque without median disposable income - 2015 model

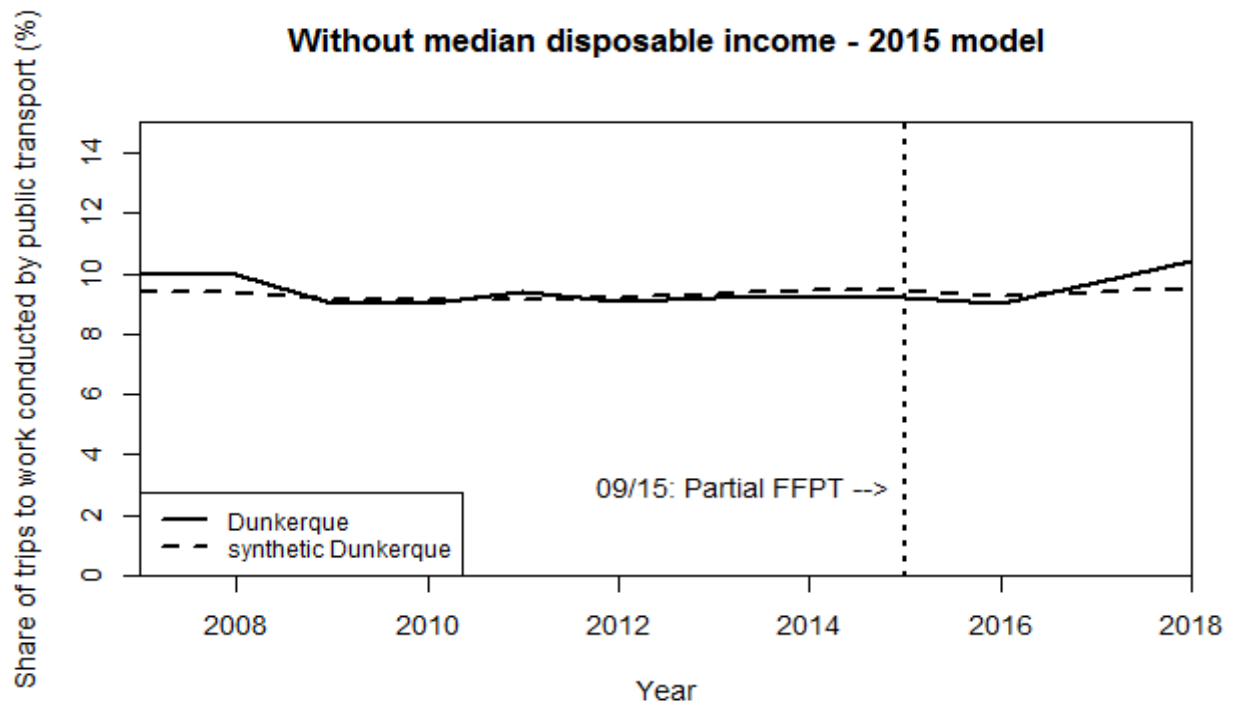
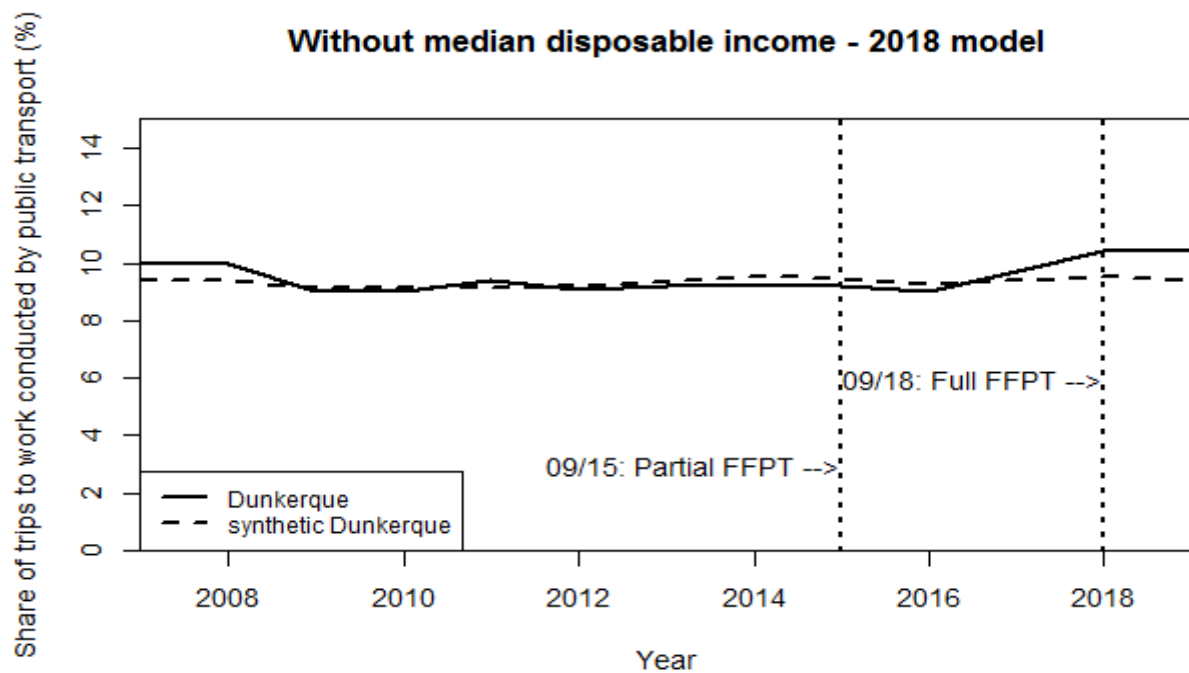


Figure 26: Dunkerque vs. synthetic Dunkerque without median disposable income - 2018 model



Annex III: Modelling other modal transport outcomes – Pre-treatment balance and in-space placebos of car models

Table 8: *Pre-partial FFPT means - 2015 car model*

Pre partial-FFPT means - 2015 car model				
	Treated	Synthetic	Donor Pool Mean	Assigned Weights
Number of daily commuters	25321.222	25297.232	28108.919	0.124
Cost 5km taxi ride	11.211	11.099	11	0.029
% Pedestrian commuters	8.022	9.528	10.275	0.016
Economic activity rate	0.424	0.423	0.43	0.298
Traffic deaths/ 10000 inhabitants	0.333	0.317	0.293	0.147
Registered cars/ 1000 inhabitants	455.333	459.398	500.869	0.277
Median disposable income	19246.222	19075.247	20087.061	0.108

Table 9: *Weights assigned to municipalities*

Assigned weight	Municipality
0.04	Annecy
0.08	Arras
0.00	Avignon
0.00	Valenciennes
0.00	Colmar
0.00	Calais
0.20	Douai
0.00	Limoges
0.00	Lorient
0.00	La Rochelle
0.03	Boulogne-sur-Mer
0.00	Vannes
0.00	Saint-Brieuc
0.20	Troyes
0.00	Martigues
0.00	Valence
0.00	Brest
0.00	Bayonne
0.00	Pau
0.00	Toulon
0.44	Lens
0.00	Perpignan

When comparing these outputs to the models estimating the PT outcomes, there is some variance regarding the weighting of predictors, with specifically the economic activity rate here playing a considerable role. However, the weights assigned municipalities largely mirror those of the PT-models, indicating that these municipalities are quite similar to Dunkerque in terms of their overall commuting split.

Figure 27: *In-space placebo test - 2015 car model*

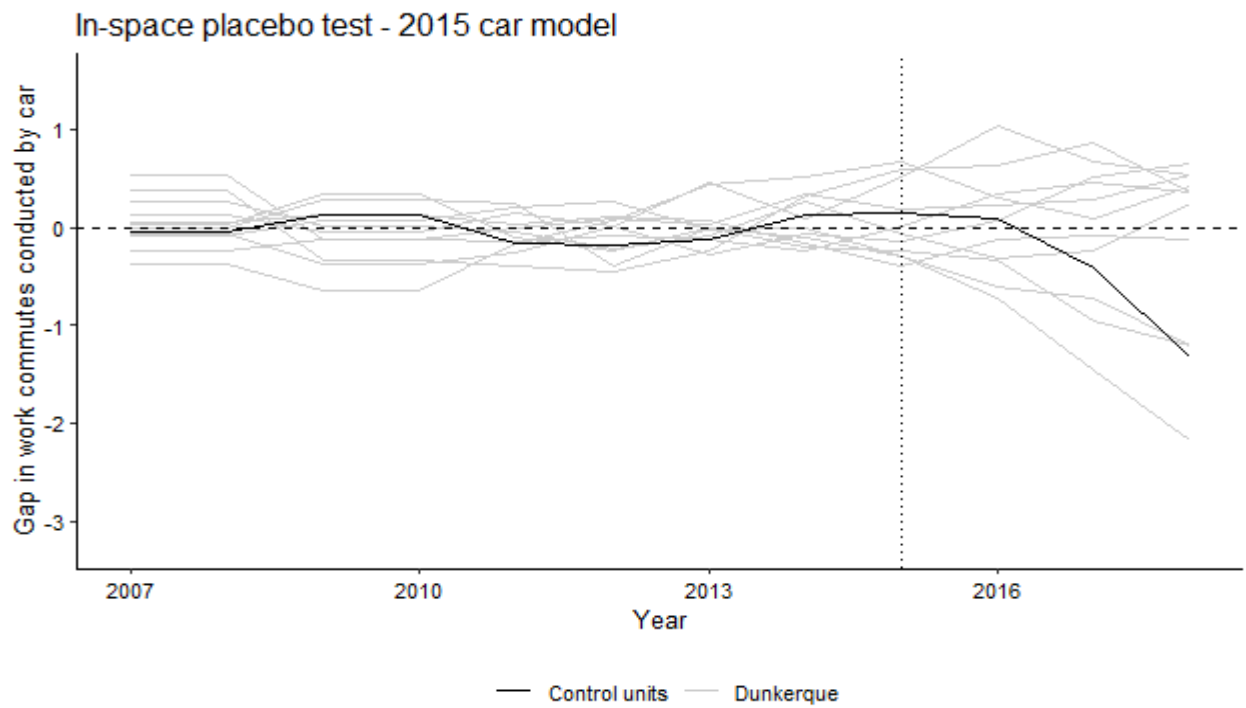


Figure 28: *Post/Pre MSPE ratio - 2015 car model*

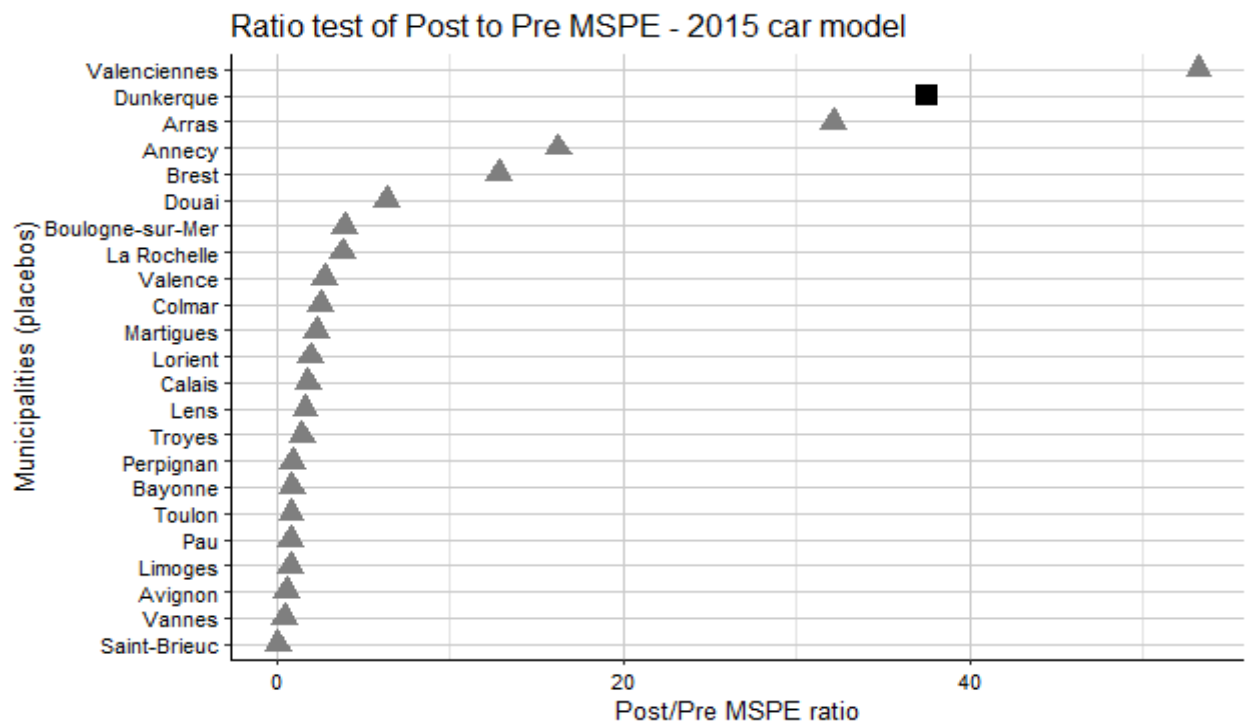


Table 10: Pre full FFPT means - 2018 car model

Pre partial-FFPT means - 2018 car model				
	Treated	Synthetic	Donor Pool Mean	Assigned Weights
Number of daily commuters	25410.909	25388.175	28373.579	0.161
Cost 5km taxi ride	11.264	11.263	11.051	0.233
% Pedestrian commuters	0.423	0.423	0.429	0.159
Economic activity rate	7.809	9.193	10.06	0.004
Traffic deaths/ 10000 inhabitants	0.273	0.271	0.26	0.233
Registered cars/ 1000 inhabitants	459.182	461.725	502.351	0.105
Median disposable income	19041.455	18999.616	19899.165	0.105

Table 11: Weights assigned to municipalities

Weights assigned to Donors	
Assigned weight	Municipality
0.10	Annecy
0.01	Arras
0.00	Avignon
0.00	Valenciennes
0.00	Colmar
0.00	Calais
0.23	Douai
0.00	Limoges
0.04	Lorient
0.00	La Rochelle
0.07	Boulogne-sur-Mer
0.00	Vannes
0.00	Saint-Brieuc
0.17	Troyes
0.00	Martigues
0.00	Valence
0.00	Brest
0.00	Bayonne
0.00	Pau
0.00	Toulon
0.38	Lens
0.00	Perpignan

Compared to the 2015 car model, it is curious that the economic activity rate does not receive much weight anymore. This could potentially hint at a certain sensitivity of results to different model specifications. However, the weight assigned to different municipalities is again similar to the PT-usage models as well as the 2015 car model, thereby again hinting at these municipalities being similar to Dunkerque in terms of modal transport outcomes.

Figure 29: *In-space placebo test - 2018 car model*

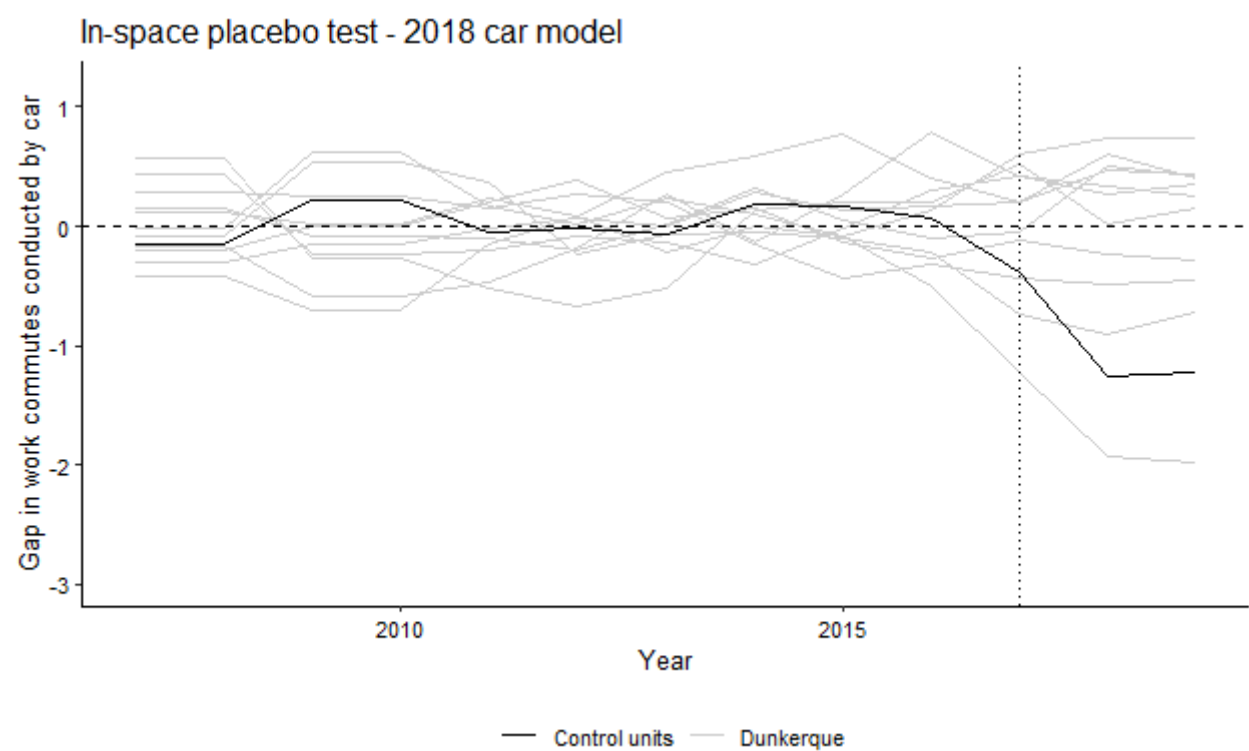
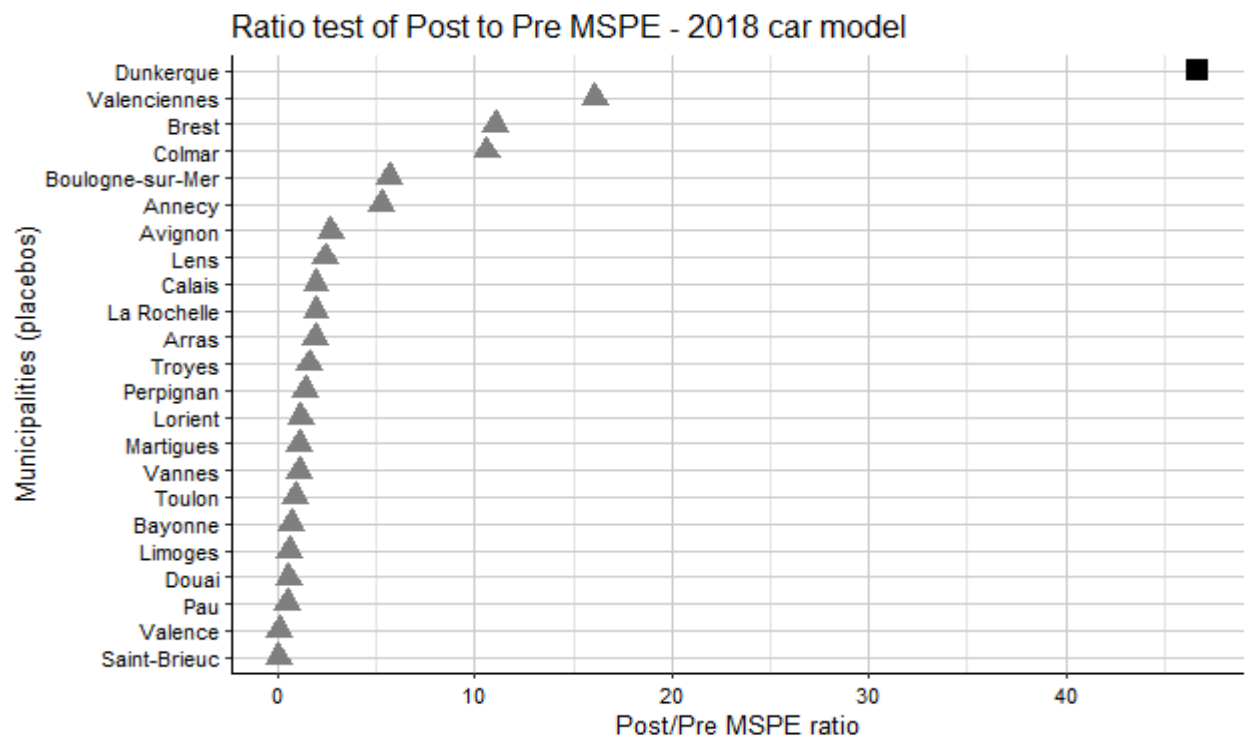


Figure 30: *Post/Pre MSPE ratio - 2018 car model*



Annex IV: Thesis Report

In defence of free-riding – Evaluating the impact of free public transportation on modes of private transport and related externalities

The case of Tallinn

Thesis Report by Marius von Frankenhorst

Word count: 6791

Introduction

The usage of cars and other private means of transport produces numerous negative externalities, especially in urban/heavily populated areas where traffic is densest; increased car-usage contributes to road-congestion (and thereby decreased mobility), higher maintenance costs of infrastructure, and increased CO₂ emissions (DESTATIS, 2022; European Environmental Agency, 2022). In 2020, private cars and motorcycles contributed to 61% of total CO₂ emissions from the transport sector -the only sector whose emissions have increased since 1990- and accounted for 81% of motorized passenger trips in the EU (*Ibid.*). Large traffic volumes also produce various adverse health effects, ranging from an increased risk of accidents and fatalities to the pollution of the environment through both noise and air pollution. Despite widespread mitigation efforts, the latter has consistently ranked among the gravest global health risks in the past 30 years, with annual estimates of attributed deaths constantly staying around the 6.5 million mark (Ritchie & Roser, 2022). Aside from increasing (industrial) economic activity, experts see the persistent predominance of private transportation as a key factor in offsetting gains made in the abatement of other sources of air pollution (such as the usage of unclean fuels for heating and/or cooking) (*Ibid.*). Consequently, the European Environmental Agency (EEA) today sees air pollution -especially in the form of exceedingly high Nitrogen dioxide (NO₂) and particulate matter (PM) concentrations- as the gravest environmental health risk in Europe, with the combustion of fuel for private transportation constituting one of the main drivers behind their prevalence at 40% of emissions (European Environmental Agency, 2022a, 2022b; World Health Organization, 2022). On a global scale, the UN estimates that 99% of the world's urban population experiences PM-concentrations exceeding WHO-limits (United Nations, 2022; World Health Organization, 2022).

Clearly, current private transportation-patterns pose a risk to citizens quality of life, as well as their -and our planet's- health as such; in recognition of this fact, the UN has made the improvement of municipal air quality a key component of its Sustainable Development Goals¹⁹, and numerous national and municipal governments have introduced a variety of corresponding mitigating measures, such as low-emission zones, completely car-free zones, or decrease parking spaces (Atlas, 2022; Cui et al., 2021; Margaryan, 2021). Other measures have aimed to increase the usage of less externality-producing transport methods, such as walking, cycling and public transportation. In case of the latter, the idea of introducing fare-free public transportation (FFPT) has gained considerable traction in recent years, but has only seen limited

¹⁹ Specifically, of SDG 11: <https://sdgs.un.org/goals/goal11>.

implementation, and remains the subject of controversial discussions regarding its potential effectiveness: Against this backdrop, this thesis tackles the following question: *To what extent does the introduction of free public transport in a city induce a modal transport-shift and decrease private transport related negative externalities such as air pollution?*

Mitigating private-transport related externalities through the promotion of less damaging alternatives via subsidizing their price seems like an intuitive idea, and partial FFPT-schemes limited to specific groups -such as pensioners and/or students (Amsterdam)- or timeframes -such as Weekends (Heidelberg and Montpellier)- are relatively widespread (Cats et al., 2014; Zhen, 2021). Germany recently ended a highly popular 3-month period of subsidizing monthly regional train tickets for 9 euro (with initial evaluations estimating that the country abated up to 2 million tons of CO₂ in this timeframe, and experienced a decrease in municipal air pollution between 6-7%) (Die Verkehrsunternehmen, 2022; Gohl & Schrauth, 2022), and suburban and regional train season tickets will be free of charge from September to December in Spain (O’Sullivan, 2022). However, the introduction of “full” -that is, non-audience, temporal or otherwise limited- FFPT has remained the exception, with only a relatively small number of municipalities having done so.

Indeed, the concept of FFPT remains contested in both policy-making and academic circles; providing (comprehensive) public transportation free of charge is highly costly, and the effectiveness of the measure is subject of controversial academic debate: To mitigate private transport-related externalities, a FFPT-scheme would need to successfully incur a modal shift in transportation, that is, induce a significant population to switch their primary means of transport from cars (or other private vehicles) to public transport. However, various authors question whether it can do so, stating that the main driver behind the dominance of private transportation is its too low cost, thereby rendering cheaper/free public transportation the second-best (policy-)option behind increasing private transportation costs (Cats et al., 2014; Holmgren, 2007). Similarly, others contend that FFPT may fail to induce car-users to shift to public transportation but will instead mainly attract individuals who previously used sustainable modes of transport such as walking or cycling (Fearnley, 2013). Indeed, existing studies on implemented FFPT-schemes have produced mixed results regarding their effectiveness, with e.g. estimates on passenger numbers ranging from negligible, over moderate, too significant increases in the short-to-medium term (Cats et al., 2017; Tomanek, 2018). However, the validity of results is often contested, particularly as -likely owing to the lack of available real world case studies- comprehensive long-term studies on FFPT effects are scarce, and subject of

methodological disputes (Cats et al., 2014; Gabaldón-Estevan et al., 2019). Moreover, while some possible outcomes -such as modal traffic changes- have received extensive academic attention, others -notably air pollution- have not, particularly in case of studies examining real-world cases.

Thus, this thesis seeks to contribute to the discussion by analyzing the case of Tallinn, which introduced a comprehensive FFPT-scheme (only excluding non-residents) in 2013, thereby allowing for the study of its effects in the medium-to-long term in a city of moderate size (~430 000 inhabitants). Specifically, the thesis aims to quantitatively estimate both the extent of the produced modal shift in transportation through the analysis of trip-shares of different modes of transportation pre-and-post intervention (1), as well as the extent to which this shift may have contributed to the mitigation of externalities associated with private transport, such as traffic accidents/fatalities, noise pollution and air pollution through the analysis of NO₂ and PM concentrations (2). It is structured as follows: The subsequent section discusses FFPT-schemes in the academic (and policy-related) literature. It is followed by a discussion of the case of Tallinn and the results of previous studies conducted on it. Based on available data sources, possible methodologies are discussed. The second half of the thesis will then involve the discussion of results regarding both (1) and (2), before the conclusion situates them within the wider body of research and discuss their generalizability and other possible implications for national and multilateral policymaking.

FFPT-schemes in the literature

Do prices even matter?

In essence, a FFPT-scheme constitutes a transport-subsidy seeking to increase demand for public transport (PT) through lowering its (monetary) consumer-cost to zero. FFPT-proponents argue that its introduction could potentially induce a so-called Mohring-effect: One of the earliest scholars analyzing the potential effect of lowering public transportation fares, Herbert Mohring argued that disutility associated with public transport mainly stems from 1) fare prices and 2) the monetary value of the time spent travelling, including waiting at stops (Mohring, 1972); thus, a service improvement capable of mitigating this disutility could spark a beneficial self-perpetuating cycle, where the mitigated disutility would induce an increase in public transportation demand, thereby necessitating an increase in supply (e.g. service frequency), which would in turn further reduce disutility through decreased waiting times, thereby leading

to a further surge in demand, etc. (Cats et al., 2014; Mohring, 1972).²⁰ To induce such an effect, introducing FFPT would thus need to increase passenger demand for public transportation.

Indeed, real-world experiences seem to indicate that citizens place a high importance on the accessibility -and therefore the price- of public transportation: Both Brazil (in 2013) and Chile (in 2019) saw the eruption of sizable protests following significant increases in bus and respectively metro-fares, in case of the latter ultimately resulting in a drive for a new constitution (Gabaldón-Estevan et al., 2019; Winter, 2017). A 2013 study conducted by the European Commission saw 59% of respondents stating lower fare prices of public transport as the most effective measure to improve urban transport, before improving the quality of services (56%) (European Commission, 2013). Interestingly, these results were stable across users of all different modes of transportation, particularly among those respondents viewing road congestion as a central impediment to urban mobility (*Ibid.*).²¹ Preceding the introduction of FFPT in Tallinn, respondents of a 2010 survey measuring public satisfaction with transportation identified too high fares as the greatest source of dissatisfaction (49%), before crowding (29%) and frequency (21%) of services (Cats et al., 2014). Evidently, whether out of social or sustainability/safety-related concerns, citizens seem to place a high importance on fare prices of public transportation in different global contexts, thereby providing promising arguments for FFPT-introduction.

However, these seemingly clear public preferences are not necessarily mirrored in the academic literature studying the drivers behind public transportation demand (elasticity), which often find prices to play a comparatively smaller role when compared to other factors. Generally, supply-factors associated with quality-of-service, such as time spent waiting for and in public transportation services, service-frequency, and total supply in terms of total distance covered, are thought to exert a higher influence on demand than prices (Brechan, 2017; Litman, 2004; Paulley et al., 2006). More importantly, most studies estimate demand for PT to fall with income (thereby classifying PT as an “inferior good”), and especially with the availability of cars (Holmgren, 2007; Paulley et al., 2006); for instance, Holmgren situates the demand-elasticity for PT connected to the availability of cars to be nearly double than that of PT prices, which remains in the inelastic spectrum (-1,48 vs. -0,75) (Holmgren, 2007). Similarly, various

²⁰ It should be noted that Mohring based his theories on calculations based on contemporary service characteristics of the bus system in Minneapolis and adjacent suburbs, and that he explicitly did not consider possible negative externalities created by an increase in bus-service frequency, such as increased traffic congestion. Nevertheless, the theorized relationship is often utilized as key arguments by proponents of free (or reduced fare) PT.

²¹ Next to road congestion (76%), decreasing air quality (81%) and an increased risk of accidents (76%) were most often named as central problems of urban mobility.

studies (Chen et al., 2011; Holmgren, 2007) view petrol prices as a strong determinant of PT-demand. Chen et. al. (2011) further report the interesting finding that public transportation demand-elasticity is strongly asymmetric, in that it responds strongly to price increases (of gasoline or public transportation), but is hardly effected by price decreases. As a result, most authors argue that increasing the cost of private forms of transportation (e.g. through higher gasoline taxes, higher parking fees in inner-city lots, road tolls etc.) is more likely to produce a substantial increase in public transportation demand than lowering fares (Brechan, 2017; Chen et al., 2011; Litman, 2004). However, while public transportation is thus generally considered to be price-inelastic, estimated elasticities vary significantly across utilized methodologies, and -more importantly- are generally thought to be subject of numerous additional factors, such as passenger-age, location (inner-city vs. rural), dependence on public transportation, time of day (peak-hour vs. off-peak), etc. (Cats et al., 2014; Litman, 2004); thus, current research does not allow for confident generalizations of PT demand-elasticity in relation to prices to be made, especially across contexts (Litman, 2004). Finally, one should note that a strong consensus exists that price-elasticity rises significantly over time, also in relation to cross-elasticity with cars; that is, a consensus exists that over time, decreased PT-fares will increasingly positively affect demand, and increasingly induce a modal shift of car/motorcycle-riders switching to public transportation (Cats et al., 2014; Fearnley & Bekken, 2006; Litman, 2004; Paulley et al., 2006). Fearnley & Bekken (2006), summarizing the findings of other authors, expect an average effect-increase on elasticity of 1.8 over time, with the final effect being visible after 5 to 7 years.

FFPT and Urban air quality

While various studies present a direct linkage between traffic volumes and/or congestion (e.g. measured in number of passing vehicles or total distance travelled) and urban NO₂/PM concentrations (Borck & Brueckner, 2018; Richmond-Bryant et al., 2017; Spuru et al., 2017; World Health Organization, 2022), and initial findings suggest that traffic-reducing policy-interventions can aid in their abatement (Gohl & Schrauth, 2022; Margaryan, 2021), studies on the specific potential of FFPT-schemes are comparatively few, and paint a more ambivalent picture.

Running a quantitative spatial model simulation, considering individual choices on place of residence (city vs. suburb), mode of transportation (private vs. PT) and domestic (non-transport-related energy) consumption, (Borck, 2019) finds that introducing FFPT and simultaneously increasing PT travel speeds decreases total pollution by 0.4%, as reduced transport emissions

are partially offset by increased domestic energy consumption resulting from increased domestic welfare/disposable income due to lower transportation-costs. In a second simulation of a city where a free public transportation system is newly constructed, total emissions fall by 1.7%, with the costs of constructing the PT-system offset by welfare-gains (*Ibid.*). These results are lower than those of Gendron-Carrier et. al. (2020), who -analyzing monthly panel data from subway openings/expansions in 58 cities-, find an average reduction of 4% in PM-concentrations. Based on their results, the authors estimate that opening a subway prevents 500 adult and 25 infant mortalities annually, and -interestingly-, that cities in the developing and developed world do not vary significantly in their response to subways, which is especially interesting given the discussed relationship between the availability of cars and PT-demand (*Ibid.*). Bauernschuster et. al. employ a quasi-experimental design by analyzing incidents of public transit strikes in Germany, thereby finding that they coincide with a 14% increase in PM-concentrations (Bauernschuster et al., 2017). Moreover, they find that instances of strikes also correlate with longer travel times and a 20% increase in traffic accident-related injuries, thereby indicating that the temporary unavailability of public transportation contributes to a significant increase of various private transport-related externalities (*Ibid.*). Recently, Gohl & Schrauth (2022) published the -seemingly- first study causally linking a price-decreasing public transportation subsidy to air pollution levels, utilizing a Differences-in-Differences (DiD) design to study the effect of Germany's 9-euro ticket on municipal air pollution via an index incorporating PM and NO₂ concentrations; they find that index-scores fell between 6-7% in the treatment-period, with results varying between week- (higher) and workdays (lower), and being more pronounced in urban areas with higher levels of PT-availability (*Ibid.*)

As their colleagues studying public transportation-demand elasticities, some scholars analyzing the relationship between FFPT and air pollution view it as a second best-option compared to raising the costs of private transport, as they fail to encourage internalization of private transport-related externalities (Borck, 2019). Nevertheless, various (quasi-experimental) studies make compelling cases that expanding and/or maintaining access to public transportation may significantly decrease air pollution and associated adverse health effects, as well as other private transport-related externalities (Bauernschuster et al., 2017; Gendron-Carrier et al., 2020). The only available study analyzing the causal linkage based on a real-world policy estimates a comparatively considerable effect on air pollution (Gohl & Schrauth, 2022). Given the divergence of opinion -and lack of causal evidence-, the current state of research thus cautions against making definitive (causal) claims between (FF)PT and the mitigation of air pollution and/or other externalities.

Previous FFPT-schemes

FFPT first emerged in the 1970's, with several cities in North America (e.g. Montreal) and especially Europe (e.g. Bologna, Dortmund and Hannover) introducing FFPT schemes to decrease gasoline consumption (Gabaldón-Estevan et al., 2019). As of 2018, 97 cities and towns worldwide had introduced “full” FFPT-schemes, --most being situated in Europe (56), the USA (27), and Brazil (11) (Kębłowski, 2018)- with Luxembourg and Malta becoming the first countries to do so in 2020 and October 2022 (Ünveren, 2022). Today, most municipalities subsidize PT to a certain extent, often encompassing partial FFPT-schemes for certain timeframes and/or groups (Cats et al., 2014; Zhen, 2021).

However, following the discussed theoretical academic literature, Real-world experiences paint a somewhat ambivalent picture concerning the success of FFPT-schemes: Prior to Tallinn, the Belgian town of Hasselt (~75 000 inhabitants), introduced FFPT for its bus-services in 1997, constituted the most prominent real-world example in Europe. Ridership increased fourfold in the first year, ultimately reaching up to tenfold the number of passengers compared to pre-FFPT levels in 2005, before remaining relatively stable until 2013 (Cats et al., 2014; Fearnley, 2013; Tomanek, 2018). However, studies indicate that only an estimated 16% of new bus-passengers shifted away from cars, with most passengers likely substituting walking and cycling with public transportation (*Ibid.*). Moreover, while Hasselt had expanded its bus fleet together with FFPT-introduction, the unexpected popularity of the measure (theoretically constituting the beginning of a desired Mohring-effect) ultimately rendered it financially unsustainable, with the Municipality reintroducing bus-fares (albeit at a comparatively cheap price of 60 cents) in 2014 (Cats et al., 2017). Although still ongoing, the FFPT-scheme in Templin, Germany (~ 15 000 inhabitants) indicates similar experiences, with overall ridership-levels of public transportation services increasing dramatically, but mostly stemming from previous cyclists and/or pedestrians, with only 10 to 20% of new passenger shifting from cars (Cats et al., 2017; Fearnley, 2013). Aubagne (France ~ 45 000 inhabitants) presents a different picture, with only an estimated 10-20% of new PT-users having previously cycled (Cats et al., 2017).

Regarding the effect of FFPT on air pollution, an evaluation conducted by the city of Stavanger (Norway, ~ 130 000 inhabitants) on its free bus scheme found no convincing effect on car-use -and thus air pollution- in its downtown areas with Bergen reporting that free bus rides had indeed replaced car-rides into the city center, but that this had at least partially been offset by new car rides towards bus stations in the suburbs (Fearnley, 2013). In virtually all cases, FFPT-introduction thus proved highly successful in generating demand -especially from young

people, pensioners and less affluent sections of society-, but seemingly failed to induce a modal transport shift, and thus a reduction of private transport externalities (Fearnley, 2013; Gabaldón-Estevan et al., 2019).

These findings seem to indicate that FFPT holds a higher potential as a social (welfare) intervention when compared to mitigating car-related externalities; however, the discussed results should be taken with a degree of caution: In most cases (excluding Hasselt), long-term effects of FFPT were not studied, and efforts to either disentangle the effects of FFPT and supply-increases or estimate causal linkages were not made (Cats et al., 2017). Apart from the Norwegian cases, most studies also did not incorporate the analysis of FFPT-effects on private-transport related externalities, instead focusing on passenger numbers, service quality and frequency, and modal transport shifts. This may partially be due to all considered cases constituting comparatively small cities or even towns, with none offering public transportation services other than buses. With a population of approximately 430 000, Tallinn remains the largest municipality to have introduced FFPT to date, thereby offering the chance to analyze the impact of FFPT-implementation in a larger context involving the provision of different types of PT-services (Kębłowski, 2018). Moreover, having introduced close to full FFPT (only excluding non-residents) in 2013, the case of Tallinn allows for consideration of medium-to-long term effects, which most academics estimate too likely be most pronounced. Given the still relatively rare nature of real-world cases of “full” FFPT-schemes, Tallin thus offers a fairly unique real-world “experiment” to study the effects of such schemes (Cats et al., 2014, 2017).

The case of Tallin

Following a public referendum with 75% of respondents voting in favor of the measure (albeit with a participation-rate of 20%), Tallin introduced FFPT for all registered residents on all public transportation services operated by the municipality on January 1st, 2013 (Gabaldón-Estevan et al., 2019). The FFPT-scheme encompassed 5 tram lines, 8 trolley bus lines (in the process of being replaced with electric buses, with currently 4 routes remaining), and 57 (75 as of 2022) “normal” bus lines (Cats et al., 2017)²²; in June 2013, it was further expanded to incorporate in-city train rides. Figure 1 depicts Tallin’s current public transit system. The decision to propose FFPT-introduction was (in part) informed by a 2010 survey in which citizens expressed the highest levels of dissatisfaction with PT-prices (49%), followed by

²² Current numbers available here: <https://www.visittallinn.ee/eng/visitor/plan/transport/public-transport>.

crowding (29%) and service-frequency (21%) (Cats et al., 2017). Prior to FFPT-introduction, a monthly transit-pass had cost 20€ (single tickets: 1€), constituting 2.5% of an average Estonians disposable income after tax (Cats et al., 2014). Indeed, Tallin's transit-services achieved 40% market share (before walking at 30% and private car at 26%) in 2012, which -while still at a comparatively high level- presented a low point following a continuous decline ever since Estonia's independence in 1990 (*Ibid.*). In the same timeframe, the motorization rate had more than doubled, reaching 425 cars per 1000 residents in 2012 (*Ibid.*). Combating this trend and inducing/maintaining a sustainable modal transportation split favoring public transportation over private cars -thereby reducing air and noise pollution- thus constituted one of the policies main goals. Furthermore, policymakers hoped to increase the (labor-)mobility of low-income and/or unemployed segments of society. Finally, FFPT should provide an incentive for registering with the Municipality, thereby increasing its income tax revenue (Aas, 2013). In preparation of and accompanying FFPT-introduction, the supply of transit-services was increased via additional priority bus lanes and an increased service-frequency, contributing to an increased link-speed of transit-services and an estimated 9% increase of total service runs, and total additional accommodation capacity of 9.6% in 2013 (Aas, 2013; Cats et al., 2014).

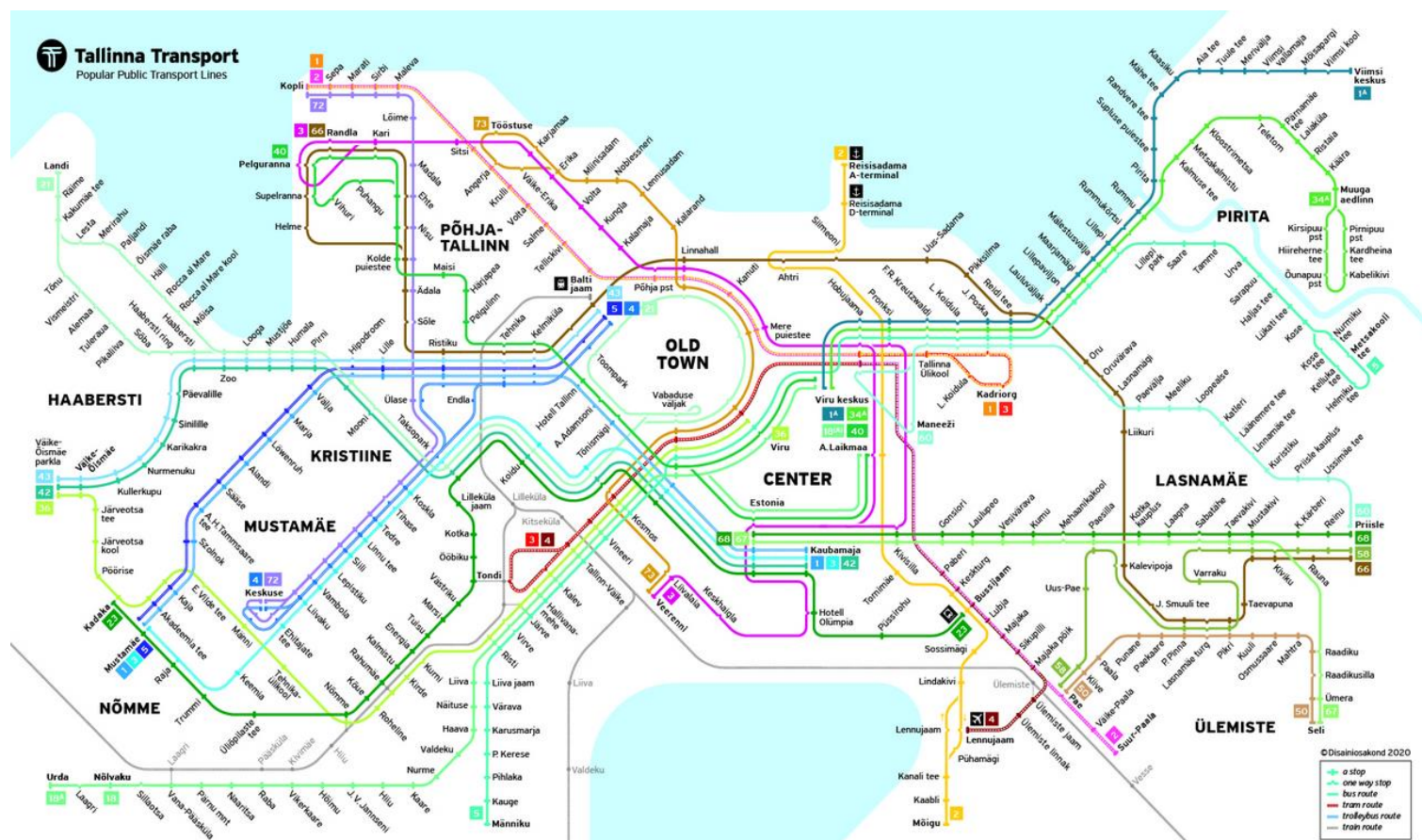


Figure 1:²³ Map of Tallin's Public transit system

Prominent evaluations of Tallinn's FFPT-scheme stem from Cats. et. al., who conducted two studies on the case, and Gabaldón-Estevan et. al.: Cats et. al. first study (2014) involved the estimation of FFPT impact on the number of boarding passengers via two separate multivariate (regression) models, prior (fall 2011 to spring 2012) and post (January to April 2013) implementation. Apart from FFPT (coded as dummy), the authors controlled for statistically significant sociodemographic (e.g. age, employment status, car-availability, etc.) and public transportation-supply (frequency of services, type of service, number of stops, etc.) factors to allow for more precise estimates about the impact of FFPT relative to other factors (see Cats et. al. 2014: 94 for a complete list of controls). The utilized data stemmed from automated vehicle location (AVL) and passenger counts (APC), collected by Tallin's public transit provider. In a later study, Cats et. al. (2017) analyzed FFPT effects on individual travel patterns -as well as other FFPT-goals envisioned by Tallinn's policymakers- based on two surveys measuring citizens satisfaction with public service provision and other socio-demographic factors- issued in late 2012 and 2013; presented to a sample of 1500 citizens, these iterations of the annually conducted survey had included additional questions covering the following (*Ibid.*):

²³ Taken from: https://www.visittallinn.ee/static/files/010/transportation_map_2020_eng.jpg.

- Mobility patterns (availability of private cars and modal usage patterns)
- Satisfaction with public transportation (overall satisfaction, frequency, etc.)
- One-day travel diaries detailing total trip-activity (start and arrival locations & times, trip mode and purpose)
- Preferred destinations for shopping and leisure
- Opinions/perceptions on general and personal impacts of FFPT

Finally, Gabaldón-Estevan et. al. (2019) applied a multi-level model to the case to shed light on its driving factors related to social and political discourse, as well as shifts in transport usage patterns.

The findings of these studies are interesting in that they partially mirror previous experiences from other FFPT-schemes, but also diverge in several aspects, sometimes from each other. Cats et. al. (2014) estimate a comparatively modest effect of FFPT on passenger demand of 1.2% when controlling for supply-changes (out of a total increase of 3%). They locate the highest increase in demand (>10%) in the Lasnamae (see Figure 1) district, which is characterized by higher unemployment, thereby reflecting previous experiences that FFPT can increase the accessibility/mobility of less affluent/ more cost-sensitive populations (including young and elderly people) (Cats et al., 2014). Gabaldón-Estevan et. al (2019) also find a comparatively modest increase in public transit-usage of approximately 10%²⁴ (excluding inner-city train rides, whose usage rose by 300%, but only accounts for 11% of total trips), with the usage of trolleybuses and trams even continuing to decline post FFPT-implementation (see Figure 2). As Cats et. al., they also report increased accessibility for lower-income populations.

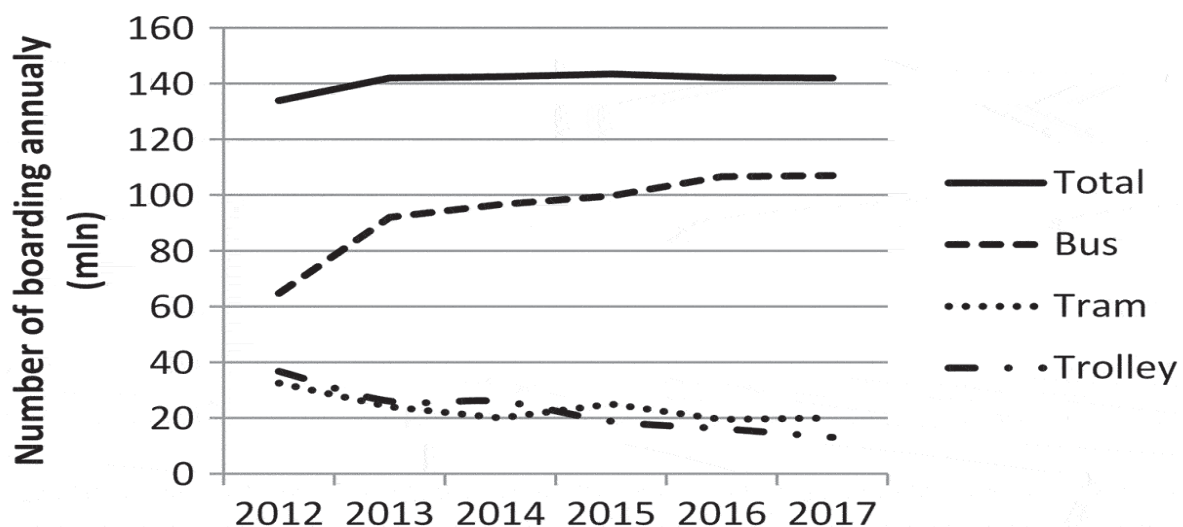


Figure 2: Number of annual boardings into different PT-services in Tallinn²⁵

²⁴ Based on descriptive observations, without controlling for supply-side changes.

²⁵ Taken from: Gabaldón-Estevan et. al 2019: 338.

Both author (-groups) also somewhat diverge in their assessment of modal transport shifts brought about by FFPT: Gabaldón-Estevan et. al (2019) see modal shifts between different PT-services (away from Trolleybuses and trams towards “normal” Buses, see Figure 2), and interpret the decreased average trip length as indicating that most new riders previously walked. Cats et. al. (2017) paint a slightly more positive picture, citing a decrease of 10% in total car trips in favor of PT, while nevertheless also estimating a decrease of 40% of pedestrians; moreover, the decrease in car travels is unfortunately also stated to be partially offset by an increased average travel distance of those still taking cars, which is attributed to changed leisure and shopping destination preferences. In total, the authors estimate an increase of 14% in PT-usage, which they attribute to the effect of FFPT steadily growing over time (*Ibid.*). Both studies report a significant overall increase in citizen satisfaction with virtually all aspects of PT-services (frequency, crowding, accessibility, etc. (Cats et al., 2014; Gabaldón-Estevan et al., 2019). Finally, it is interesting to note that contrary to previous experiences, Tallinn’s FFPT-scheme seems to have proven financially sustainable, with the municipal income tax generated by new registrations (€10 million) almost offsetting the incurred cost (€12 million) (Cats et al., 2014).

Gabaldón-Estevan et. al (2019) provide a brief discussion of possible FFPT-effects on NO₂ and PM(10)-concentrations (see Figure 3). According to the authors, sufficient data on private gasoline consumption is not available to allow for accurate interpretations of these figures; nevertheless, one can see a constant recession of PM(10) concentrations in the city Centre - which would be expected to experience highest traffic-related concentrations- after 2013. The trend for NO₂ is different, with the authors stating that the post-2015 increase could possibly be linked to car-chains damaging streets in winter and leading to more air pollution, although cautioning for a careful interpretation of the figures due to a lack of meteorological data.

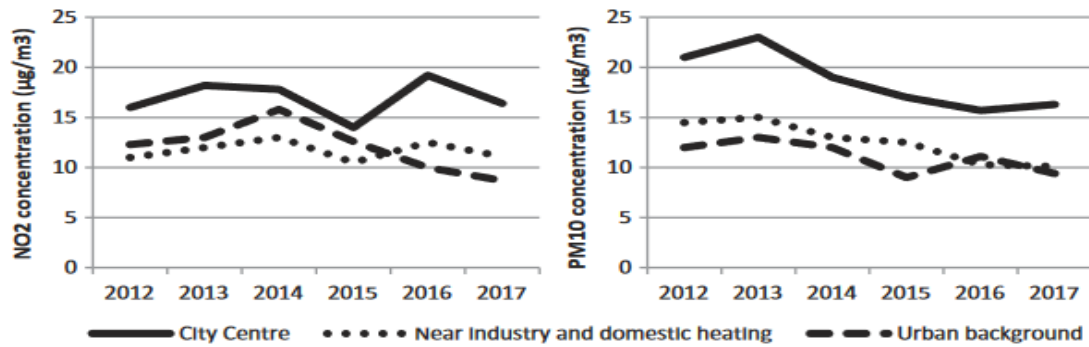


Figure 3: NO2 and PM10 concentrations in Tallinn 2012 - 2017²⁶

While undoubtedly providing interesting insights, the discussed studies nevertheless call for future research: While Gabaldón-Estevan et. al. provide a comprehensive account of FFPT-effects in Tallinn in the mid-term, they do so based on a more descriptive methodology, thereby providing no causal estimate of FFPT-effects. Conversely, the studies of Cats et. al. offer a more convincing methodology in this respect, especially as they disentangle FFPT and supply-increase effects- but only consider the short term. None of the studies extensively considers possible effects on private transport-related externalities. Thus, the methodology proposed in the subsequent section aims to ultimately provide results which allow for a more confident (causal) linkage of FFPT to several quantifiable outcomes of FFPT, also in the medium-to-long-term.

Methodology & Data

This paper seeks to analyze the effects of FFPT-introduction on private transport/car-related externalities in Tallinn-specifically including the medium-to-long-term. To do so, the following hypotheses are derived from its underlying research question, and reflect what should be observable under the assumption that FFPT-schemes can mitigate private-transport related externalities via the induction of a modal transport shift:

- H1: *Introducing free public transport reduces the share of trips conducted by private means of transport (cars and motorcycles) relative to public transport (all services covered by Tallin's FFPT-scheme).*
- H2: *Introducing free public transport reduces traffic-congestion, and therefore average travel times.*
- H3: *Introducing free public transport reduces traffic accidents and resulting fatalities.*
- H4: *Introducing free public transport reduces noise pollution.*

²⁶ Taken from: Gabaldón-Estevan et. al 2018: 340.

- H5: *Introducing free public transport reduces average concentrations of traffic-related air pollutants (NO₂ and particulate matter (PM)).*

Figure 4 presents the -somewhat simplified- causal graph behind this assumed relationship.

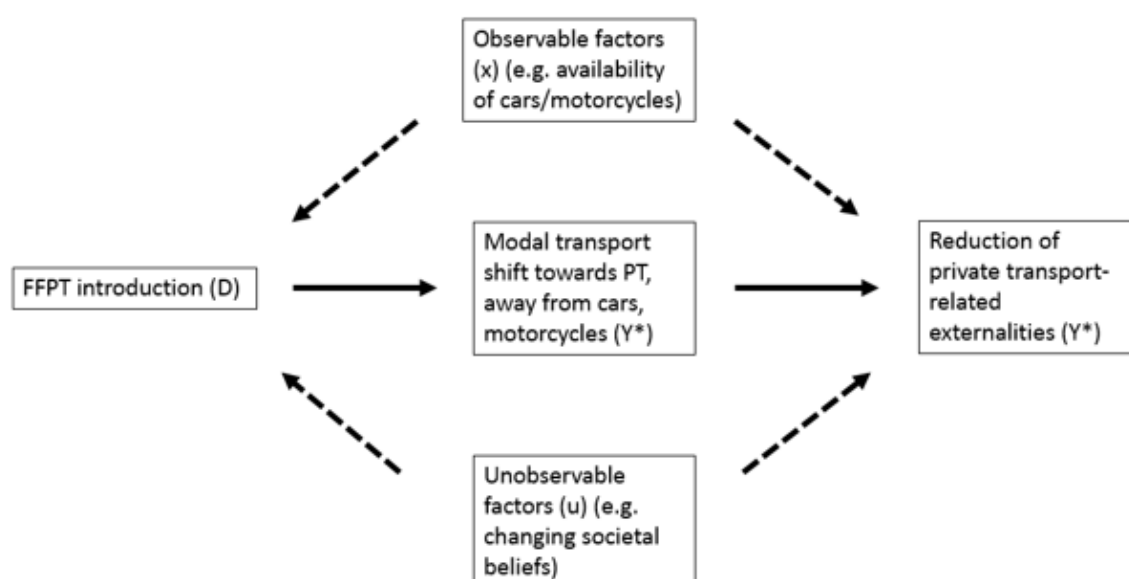


Figure 4: Causal Graph depicting the assumed relationship between FFPT and externality-reduction

Due to figure 4 depicting the assumed causal relationships underlying separate Hypotheses,²⁷ and (especially) the complexity of (observable and unobservable) drivers behind modal transport shifts and car-related externalities, it should not be understood as a comprehensive depiction of the assumed causal process, but rather as an approximation indicating the general assumed relationship, and underlining the argument for a methodology capable of disentangling the (causal) relationship of treatment (FFPT) and outcome(s) from the multitude of other observed (X) and unobserved factors (U) at play. A likely example of the former would be the availability of cars/motorcycles commonly assumed to influence modal transport shares. Regarding unobserved factors, it e.g. seems valid to assume that changing societal beliefs/values towards sustainability could influence both modal transport shifts and private-transport-related externalities (e.g. through an increased prevalence of electric cars).²⁸ Given the multitude of factors potentially influencing (parts of) the relationship, it thus seems advisable to employ methodologies capable of controlling for them so as to arrive at an as

²⁷ The dependent/outcome variable is noted twice as Y*, as depending on the hypothesis in question, it either relates to the modal transport shift (H1), or a specific form of private-transport related externality (H2-4). In the later case, the modal transport shift presents more on an intervening variable (since it is caused by the treatment of FFPT-introduction, and ultimately causes the externality-mitigation), although it is observable.

²⁸ Indeed, such changing values could even exert in influence on the decision to introduce the treatment of FFPT as such, thus constituting a possible unobserved confounding variable. Naturally, observable factors could also constitute confounding variables.

accurate as possible estimation of the causal outcomes associated with FFPT. The selection of methodology is however also dependent on the available data.

Data

Presently, most available data stems from Eurostat, specifically from statistics on “Cities and greater cities”.²⁹ In this data repository, Eurostat compiles indicators related to the quality of

Table 1: (Tentative) list of considered (outcome) variables – Eurostat and EEA	
Variable Name	Description and Coding
TT1012V (H1)	Share of journeys to work by car or motorcycle in %
TT1010V (H1)	Share of journeys to work by PT (rail, metro, bus, tram) in %
TT1007V (H1)	Share of journeys to work by bicycle in %
TT1008V (H1)	Share of journeys to work by foot in %
TT1019V (H2)	Average time of journey to work in minutes
TT1060V (H3)	Number of people killed in road accidents
EN2033I (H4)	Proportion of residents exposed to road traffic noise >65 dB (daytime)
EN2035I (H4)	Proportion of residents exposed to road traffic noise >65 dB (nighttime)
EN2026V (H5) (complemented with EEA airbase data post-2013)	Annual average concentration of NO ₂ (µg/m ³)
EN2027 (H5) (complemented with EEA airbase data post-2013)	Annual average concentration of PM ₁₀ (µg/m ³)

Urban life from close to 900 municipalities within the EU, thereby covering general statistical metrics regarding e.g. population, but also transport and environment. All indicators are measured on an annual basis, with the dataset nominally covering the timeframe of 1989 – 2022, although this varies between different municipalities and indicators. Most indicators are reported by the respective national statistical agencies, with those likely relevant as outcome measurements summarized in Table 1. In case of NO₂-concentrations, Eurostat data is complemented with EEA data, which took over reporting average NO₂-concentrations through its Airbase-database from 2013.³⁰

These indicators -specifically regarding those associated with H1 and 2, represent approximations of the respective outcome of interest, as they measure trip-metrics associated with trips to work, rather than all conducted trips. Given that (pre-Covid), trips to work likely constituted a significant share of an individual’s total conducted trips -as also indicated by the divergent effects of lower-cost PT on air pollution on weekend- vs. weekdays by Gohl &

²⁹ Available here:

<https://ec.europa.eu/eurostat/databrowser/explore/all/general?lang=en&subtheme=urb&display=list&sort=category>. Description of the databases and partial codebook available here:

https://ec.europa.eu/eurostat/cache/metadata/en/urb_esms.htm.

³⁰ Available here: <https://www.eea.europa.eu/data-and-maps/dashboards/air-quality-statistics>.

One should note that the EEA breaks down air pollutant measures into values recorded in “Traffic”, “Industrial” and “Background” (=residential) areas, whereas Eurostat did not. To allow for the comparison of pre- and post-2013 measurements, I will need to find out which measuring stations the Eurostat values were based on.

Schrauth (2022)- it seems valid to argue that they should nevertheless allow for fairly accurate measures of FFPT-impacts on Tallin's modal transport split (H1) and congestion (H2); nevertheless, they still omit a share of trips made, thereby detracting from the overall validity of prospective results. Moreover, they also naturally exclude trips made by non-working individuals, which are likely to profit especially from FFPT-introduction.³¹

Such concerns could potentially be alleviated by accessing more “granular” data provided directly by Tallinn and/or Estonia's statistical agency. As previously discussed, Cats et. al. (2013, 2017) utilized data on PT-passenger numbers, and trip-lengths, as well as sociodemographic controls stemming directly from Tallinn's PT provider and the municipality.³² Estonia's statistical agency collects information on pollutant-emission and transport-related indicators, and could thus potentially also constitute an interesting source for e.g. the share of total trips conducted by different means of transport (although it is unclear whether such data is available on the municipal level, as it is not mentioned on the corresponding webpage.³³ The Agency provides a mask for submitting data-access requests,³⁴ through which I will inquire whether such data would be available. To potentially access the data utilized by Cats et. al. -also for post-2013- I will contact the Municipality of Tallinn, which seems to be possible via its website.³⁵ Based on the final availability of data, the most pertinent methodology might change. Thus, I will briefly discuss alternatives based on potentially available “granular” data from Estonian authorities in the following section, but note that presently, the already available data naturally presents a more secure basis on which to design my methodology.

Methodology

While the ultimately employed methodology may vary according to data-availability, it is certain that the timeframe of analysis will end in 2019, as the Covid-19 pandemic and associated

³¹ As this relationship is comparatively well established in existing literature, it may not constitute a model-breaking omission, but should nevertheless be noted.

³² The data specifically covering individual transport choices and travel diaries pre- and post-FFPT-implementation was unfortunately only levied in 2012 and 2013, and is thus not usable for a longer term study.

³³ Link: <https://www.stat.ee/en/find-statistics/statistics-by-region>.

³⁴ Link: <https://www.stat.ee/en/find-statistics/request-statistics>.

³⁵ Link: <https://dhs.tallinn.ee/atp/?id=1256>.

response-policies greatly affected transport-patterns and thus virtually all outcomes under consideration.³⁶

To estimate the causal linkage between FFPT-implementation and my outcomes of interest, I can utilize the fact that Tallinn's FFPT-implementation in some ways constitutes a natural experiment within the EU-context; namely, while Tallinn received the treatment of FFPT (D), (most) other European municipalities did not. Given the availability of data from close to 900 municipalities, this should allow for the implementation of (a series of) Difference-in-Difference (DiD) models. This method entails the comparison of a treatment (Tallinn) and control (other EU municipality) group which satisfy the parallel trend assumption, meaning that pre-treatment, both cases exhibited the same trend, thereby allowing for the assumption that in absence of the treatment, they would continue to do so. For this paper, it can be described via the following equation:

$$Y_i = \beta_0 + \beta_1 \text{Tallinn}_i + \beta_2 \text{Post2013}_i + \beta_3 (\text{Tallinn}_i \times \text{Post2013}_i) + \epsilon_i$$

Y_i describes the i th respective outcome under study. β_0 is the intercept term. $\beta_1 \text{Tallinn}_i$ identifies whether the unit is treated (and thus Tallinn = 1) or control (other Municipality = 0), with $\beta_2 \text{Post2013}_i$ identifying whether the outcome was measured in the pre-treatment (pre-2013 = 0) or post-treatment (post 2013, including 2013 = 1) phase. Interacting the treatment and time-indicators $\beta_3 (\text{Tallinn}_i \times \text{Post2013}_i)$ then provides the DiD-estimate for coefficient β_3 . ϵ_i encapsulates the error term of the factors the model fails to predict. If the parallel trend assumption can be satisfied, this model provides an estimate of the causal effect of FFPT-introduction on Y in terms of the difference to Y's outcome if FFPT had not been introduced. To provide further robustness, a placebo-test, for example by shifting the date of FFPT-introduction to 2012, can be performed.

The advantage of this methodology is that it can provide a causal estimate of Y free of biases introduced by unobservable factors, such as inherent differences between Tallinn and the control-municipality, or changes influencing the outcome of Y in both Tallinn and the control-municipality between pre- and post-treatment period. However, the validity of assuming parallel trends in the post-treatment phase will diminish with increasing temporal distance from FFPT-introduction, as unit-specific time-variant changes, such as a further externality-reducing policy intervention specific to the control-municipality post-2013, may occur. While the fact

³⁶ For instance, Covid-lockdowns and the associated drop in traffic greatly decreased NO₂- and PM-concentrations throughout the EU (European Environmental Agency, 2020).

that both considered municipalities are part of the EU may provide a degree of “protection” against this occurring, it will be necessary to analyze whether such changes may have taken place. Moreover, this methodology will not allow for differencing between the effects on Y produced by the FFPT-implementation and the simultaneous expansion of PT-services and will show the effect of both together.³⁷ Likewise, continuous supply-changes in Tallinn post 2013 (albeit small) may further decrease the validity of estimates, at least if the control municipality did not also increase public transit supply. Finally, given the seeming complexity surrounding private-traffic patterns and associated outcomes in different contexts, the generalizability of results may not be substantial.

Air pollution and the Synthetic Control Method

As one of the main drawbacks of the DiD-method, it is worthwhile to consider a methodology which does not rely on the fulfillment of the parallel-trends assumption, specifically post-treatment; namely, the synthetic control method. Rather than finding a control case exhibiting parallel trends on the outcome variable pre-treatment, this method builds on constructing an artificial counterfactual of the treatment-group, which matches the trend of the outcome variable pre-treatment, and thus allows for the identification of the treatment effect by modelling an artificial trend for the treatment-group if it hadn't experienced it. While theoretically applicable to all outcomes of interest, I briefly discuss the method in relation to measuring FFPTs introduction on air pollution, specifically on NO₂-concentrations.

To create the artificial counterfactual (=the synthetic control), several weighted predictors commonly associated with NO₂-concentrations are combined until the resulting pre-treatment trend mirrors that of Tallin as closely as possible. For this to be successful, it is important to have data for both Tallinn and the municipalities providing predictors for as many years prior to the treatment as possible. In case of NO₂-concentrations, 12 consecutive annual observations prior to FFPT-implementation are available (2001-2012, with observations for 1997 and 1998 also available). Based on the reviewed literature, likely candidates for predictors are variables measuring (the amount of) traffic and/or availability of cars in a city, as well as meteorological

³⁷ I am wondering whether this could potentially be alleviated by controlling for PT-supply changes in the equation, and potentially interacting them with year-fixed effects (similar to the way Gohl & Schrauth (2022: 6ff) controlled for changes in fuel prices in their study on the effects of Germanies 9-euro ticket on air pollution). However, I am unsure whether I have the necessary data for this, as Eurostat does not provide measures for the supply of PT (other than total length of bicycle lanes) on the municipal level. Similar considerations could be made for models pertaining to specific outcomes, such as air pollution, which is often linked to meteorological factors (see section on synthetic control method).

variables³⁸ (Malley et al., 2018; Richmond-Bryant et al., 2017; Spuru et al., 2017). Traffic-related variables noted in table 1, as well as additional Eurostat-indicators (e.g. people commuting in and out of a city on a daily basis, number of (registered) private cars) could account for the former, whereas meteorological indicators such as average precipitation, windspeed and temperature could partially stem from Eurostat and be complemented by data from the European Climate Assessment & Dataset project.³⁹ If successfully implemented, a fairly strong case for treatment and control group only differing in the reception of the treatment could be made, thereby allowing for a fairly confident statement about the causality of the results. Again, placebo-test such as changing the treatment-time could provide robustness for produced estimates. While relying on less strong assumptions about post-treatment trends than DiD, the synthetic control method would otherwise face similar disadvantages in not being able to disentangle supply-side changes from FFPT-introduction.

Disentangling the effects of FFPT-introduction and supply-side changes

Given that both discussed methodological approaches will likely face issues in disentangling the effects of FFPT-introduction from those of an increase in public transit supply, it could make sense to complement them with a multivariate analysis (similar to Cats et. al. (2013)) controlling for the later (and other observable factors). This would specifically benefit from access to more specific data from Tallinn and/or the Estonian statistical agency.⁴⁰ While this method could be affected by Omitted variable bias stemming from unobservable factors influencing the relationship and therefore could not provide confident causal linkages, the combination of both approaches could benefit the understanding of what role FFPT specifically can play in reducing private transport-related externalities. This could be especially valuable given previous studies general focus on modal transport shifts rather than externalities. However, the space-constraints lead me to believe that doing both would require somewhat scaling back the considered outcomes in favor of more in-depth analysis.

³⁸ Since I will analyze yearly averages, it is possible that meteorological factors could average out over time, but given their prevalence in the literature, it nevertheless seems pertinent to include them at least potentially in the discussion.

³⁹ Available here: <https://www.ecad.eu/>.

⁴⁰ This could naturally also be done with Eurostat data, but the partial approximation of outcome variables (in favor of including data from various municipalities) leads me to believe that doing so would dismiss this datasets biggest advantage (comparability) while maintaining its weakness (case-accuracy).

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