Fare-Free Public Transportation effects' assessment on French economy.

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Dissertation written under the supervision of Benny Geys.

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ABSTRACT

This dissertation uses a single event - the implementation of Fare Free Public Transportation (FFPT) in 140 French cities between 1965 and 2018 - to measure thanks to a staggered Difference-in-Differences regression approach, the socioeconomic effects of this policy. The treatment group includes all cities with FFPT. The control group represents all other cities with a public transport network. Our work consisted in the verification of 3 hypotheses: first, free public transport reduces unemployment in the cities concerned. Second, it makes these cities more attractive. The population rate changes are more favourable (said differently, population is growing more or shrinking less) in those places compared to the control group. Finally, this policy would reduce the number of cars per household. Three main lessons can be drawn for this work. First, we found a reduction in unemployment of 0.517% on average when the city has implemented FFPT for more than 5 years for the active population 15-64-years-old and up to -18% unemployment for all municipalities for the 25-54-years-old. This is consistent with our hypothesis. Second, we found no statistically significant effect of FFPT on population growth in city. This frown on our second hypothesis. Finally, our findings indicate a slight but statistically significant impact of FFPT on household's car ownership (-0.8%). Thus, this confirms the third hypothesis.

Keywords: Prices, public transit, unemployment, population growth, cars ownership, public policy, transport infrastructures, difference-in-differences.

Avaliação dos efeitos dos Transportes Públicos Gratuitos na economia Francesa.

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Supervisor: Benny GEYS (BI Norwegian)

Resumo

Esta dissertação utiliza um único evento - a implementação do Transporte Público Sem Tarifas (FFPT) em 140 cidades francesas entre 1965 e 2018 - para medir, graças a uma abordagem de regressão escalonada da Difference-in-Differences, os efeitos socioeconómicos desta política. O grupo de tratamento inclui todas as cidades com FFPT. O grupo de controlo representa todas as outras cidades com uma rede de transportes públicos. O nosso trabalho consistiu na verificação de 3 hipóteses: primeiro, o transporte público gratuito reduz o desemprego nas cidades em questão. Segundo, torna estas cidades mais atractivas. As alterações na taxa de população são mais favoráveis (dito de forma diferente, a população está a crescer mais ou a diminuir menos) nesses locais, em comparação com o grupo de controlo. Finalmente, esta política reduziria o número de carros por agregado familiar. Três lições principais podem ser tiradas para este trabalho. Primeiro, encontramos uma redução do desemprego de 0.517% em média quando a cidade implementou a FFPT durante mais de 5 anos para a população activa de 15-64 anos e até -18% de desemprego para todos os municípios para os 25-54 anos. Isto é consistente com a nossa hipótese. Em segundo lugar, não encontramos qualquer efeito estatisticamente significativo da FFPT no crescimento da população na cidade. Este desaprovamento da nossa segunda hipótese. Finalmente, as nossas conclusões indicam um impacto ligeiro mas estatisticamente significativo da FFPT sobre a propriedade do automóvel do agregado familiar (-0.8%). Assim, isto confirma a terceira hipótese.

Palavras-chave: Preços, trânsito público, desemprego, crescimento populacional, posse de automóveis, política pública, infra-estruturas de transporte, diferenças entre as diferenças.

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I) Introduction :

1) Context

In December 2019, the European Commission presented the European Green Deal. With this initiative, the Commission wishes to seize the climate crisis as an opportunity to push for a European economic, social, and environmental project. The main objectives of this project are the drastic reduction of greenhouse gas emissions by 2050, an inclusive economic growth strategy and increased independence vis-à-vis natural resources. The “Smart and Mobility Strategy” is an important part of this European Green Deal. Through this particular program, the Commission wants to improve urban and peri-urban life for European citizens through a number of ways.

First, by reducing congestion and decreasing greenhouse gas emissions. In Europe, 25% of greenhouse gas emissions come from the transportation sector (*European Commission*, n.d.). In France, this number lies even higher since in 2019 the transportation sector weighed in at no less than 31% of total greenhouse gas emissions in the country, with 53% of that (or roughly 16% of total emissions) coming from the car (*Haut Conseil pour le Climat*, 2021). Second, by promoting public transport and making it fairer and more inclusive for all people. As has been repeatedly pointed out, cities today are built predominantly to cater for the needs and life-style of healthy men in their forties (Štraub & Jaroš, 2019). However, this city design can have important consequences for those who cannot afford the means of transportation preferred by this specific group, which will imply that these groups are thereby partially excluded from full integration into (modern urban) society.

The unfortunate geopolitical events of the beginning of this year 2022, namely the war that is looming at the European gates, furthermore show that it has become increasingly bad to be dependent on fossil fuel intensive infrastructure. It is therefore necessary to propose and implement alternative means of transportation, especially for the poorest households who will continue to suffer if no actions are taken.

2) Thesis objective

In this thesis, we will discuss one of the options that many European cities have considered and/or are considering to address these challenges, namely Fare-Free Public Transportation (FFPT). In the following parts, we will see that FFPT is often viewed as a hard-to-define policy proposal, and that its social, economics and environmental implications remain poorly understood. As a result, FFPT is sometimes quite controversial and heavily debated. Even so, while everyone has an opinion about it, these opinions are rarely based on in-depth and critical scientific reflection and empirical analysis of available data (Delavoye et al., 2022). A central mission of this thesis will be to take many of the arguments arising in existing debates as a starting point, and evaluate them with the use of available data from France.

We will thereby draw extensively on several academic literatures evaluating the economic effects of improved transport infrastructure and accessibility. In fact, FFPT can be thought of as a means of easing mobility accessibility via a decrease in its price (as faced by the user). Since FFPT has been implemented at different points in time in different places in France over the five decades (since its first introduction in 1971; see below), we can evaluate its impact by comparing places with and without FFPT before and after FFPT has been implemented. This means that we will apply a difference-in-differences method to estimate FFPT's impact. We will more specifically implement this research design to assess the potential effect of FFPT on unemployment (as an indicator of social inclusion and economic development), the number of cars per household (as an indicator of FFPT's environmental impact), and finally on population growth (as a measure of the impact of FFPT on the attractiveness of cities and its possible value to citizens). The choice of these variables was driven largely by data availability, and will be defended in more detail later in this thesis. Therefore, the main research question addressed throughout this master thesis is:

> *What is the effect of the introduction of Free Fare Public Transport (FFPT) on economic, environmental and socio-demographic outcome variables in French municipalities over the period 1968-2018?*

The rest of the thesis will be structured as follows. In the remainder of this introduction, we will first introduce and define the concept of Fare-Free Public Transportation and describe the current situation of FFPT in France. In the next chapter, we will go through relevant academic literature to gain insights into the likely effects of introducing free public transport and/or developing new public transport infrastructure. Then, we will introduce our main theoretical arguments to understand how FFPTs can influence our variables of interest (i.e. unemployment, population growth, and car ownership). Subsequently, we will present the data available to us, both in terms of their key sources and the descriptive statistics. In the penultimate chapter, we will build our difference-in-differences regression model taking inspiration from earlier studies in the field, and present as well as discuss the main findings deriving from these models. Finally, we will offer a conclusion that also opens the debate on the future of the research in this field.

3) Fare-Free Public Transportation definition

FFPT refers to a system of transportation running by cities or group of cities, that does not involve any direct cost for the users (such as purchasing of transport tickets). The name FFPT has been preferred to other names such as Free Public Transportation. The reason is that, even though it does not cost anything to the user, there is a shared cost for the society to carry (e.g., by households, cities, and/or companies) in order to maintain and finance the network. FFPT has been implemented in a number of different ways in different places. It can be unconditional in the sense that is it free for everyone at all times. In this case one can talk of "full FFPT". Partial FFPT also exist. Partial FFPT can be spatially limited, in which case the network is free only in some part of the city. It can be socially limited, in which case it is freely accessible only to some parts of the population such as senior, young or unemployed people. Or it can be temporally limited, such as during the COVID-19 outbreak in many cities in the US (Kębłowski, 2020) or during the pollution peaks as it is the case in some cities in France (Contard, 2019).

Partial free public transport tends to affect a particular period, category of population or city perimeter. Incorporating all forms of free public transport in our work, partial and total, would tend to increase the number of observations and thus improve the estimates' accuracy. In the other hand, it will also tend to disturb the clarity of our estimates as we would mix different option and intensity in the treatment group (partial FFPT is likely to be less intense and trigger lower effects).[1] Thus, we will focus on total free access in this study. Studying partial free rides could be the object of a future research work.

[1] Further details in the treatment accuracy discussion present in the methodology part of this study.

4) Fare-Free Public Transportation historical and current situation in France

As mentioned previously, we are going to carry out the study in France. In this country, the first appearance of free fare public transport is to be attributed to Colomiers in 1971[2]. This policy remained relatively marginal until the end of the 2000s, when the number of cities wishing to adopt this approach to organizing public transport intensified. The arguments put forward by these recent adopters are, among others, that FFPT would allow for greater efficiency of public transport service provision, greater social inclusion, reduced congestion on the roads, positive effects on the promotion of public transport and, finally, the reduction of greenhouse gas emissions. The less populated free public transit network is counting 6,500 inhabitants (Saint-Flour). At the opposite, the most populated network is Dunkirk and its vicinity, with almost 200,000 inhabitants. As of the time of writing this master thesis in 2022, there are 37 groups of cities that have adopted a complete free service scheme.[3] The latest to do so have been Douai's agglomeration (North of France), which counted 149,000 inhabitants in 2018.

While FFPT was originally implemented mainly in relatively smaller cities, more recent years have seen the appearance of bigger cities in the implementation of this policy, such as Aubagne and its suburbs in 2009 (100,000 inhabitants), or Dunkirk (200,000 inhabitants) in 2018. In 2023, the Montpellier Méditérranée Métropole public transport network (480,000 inhabitants) is scheduled to go free-of-charge for all users. The map below shows the complete overview of all 37 places in France where 'full' FFPT has been implemented thus far. The figure shows that a considerable variety of cities of distinct sizes is represented in the FFPT universe. Importantly, the map also indicates that there exists some limited clustering of FFPT places in the north of France. Overall, however, there is a very even distribution of FFPT places across the entire French territory, and almost all major regions of France have at least one city with FFPT.

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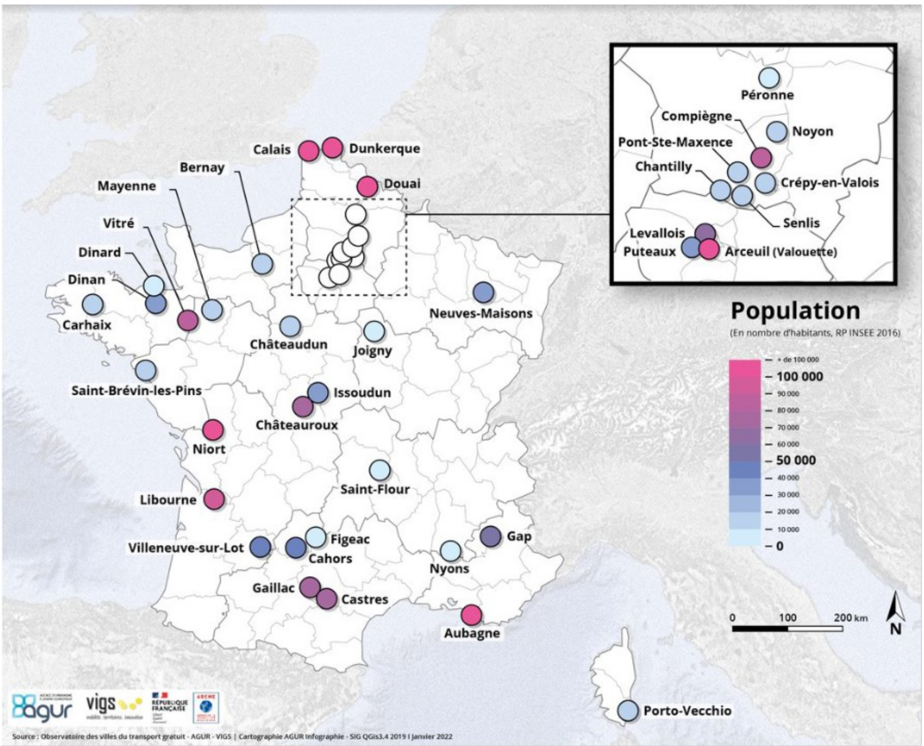
[2] Colomiers ended this policy in 2016. It has been obliged to do so by law, as urban transport is not the responsibility of the city anymore.

[3] Note that we refer to 'groups of cities' here since many places in France are providing joint public transport services. Hence, public transport networks tend to cover more than one municipality. As a result, the introduction of FFPT in one such transport network will generally also by construction affect more than one municipality. We will return to this later in chapter 4 when describing the main detasets and operationalizations employed in the analysis.



Map : Cities that have implemented FFPT in France by number of inhabitants, in January 2022. Source : Observatory of cities and free transport (France).

The decision to implement this policy measure did not come solely from identified political socialist parties. Indeed, of the 37 free network cities, 19 cities are identified as right-wing, while 17 are identified as left-wing (Delavoye et al., 2022).

During the 2020 mayor elections, free public transport was proposed in many cities (more than 100), with a large concentration of propositions in the North. Sometimes, FFPT was even present in several electoral programs inside a same city, such as Bordeaux (250,000 inhabitants), Toulouse (472,000), the Lyon Métropole (1,400,000 inhabitants), or the Montpellier Méditerranée Métropole that is turning free-of-charges following the victory of Michaël Delafosse (Socialist Party) in the last municipal elections in 2020, whose FFPT measure was included in his campaign promises (Delavoye et al., 2022).

The specificity of the free networks lies in the fact that most of them only consist of bus lines. Only Aubagne has a tramway line, which is only 3 kilometers long. Nevertheless, Montpellier with its 60 kilometers of tramway (4 lines) will constitute a real revolution in the French free transit landscape.

5) Socio-demographic variable evolution in France from the end of the 60s to nowadays

Our variables of interest change substantially over time. Putting them into perspective in their respective historical and economic contexts will allow us to better understand the rest of this work.

a) Unemployment

At the end of World War II, France was rebuilding. Unemployment was very low, and growth was rapid until the mid-1970s. This period is called "les Trentes-Glorieuses" (The Glorious Thirthies). The successive oil shocks of 1973 and 1979 marked the end of this period. Since 1985, unemployment in the country has been fluctuating between 7 and 10.5%.

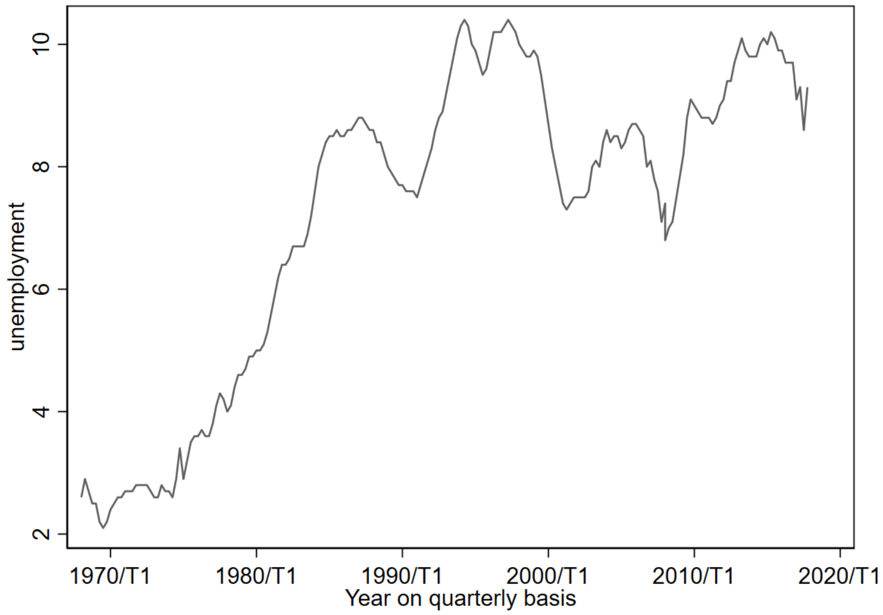


Figure 1 : French unemployment from 1968 to 2018 at quarterly basis. Data : INSEE.

b) French population

After the WWII, the country has known a rapid growth of population, due to work immigration and the baby-boom. This stopped in the mid-1970s. Since then, growth has remained steady (0.5% average growth per year) and relatively steady in its composition (80% from natural balance). This is largely due to the increase in life expectancy. At the city level, the dynamics are disparate. In 2017, the population of Paris and its region grew at the same rate as the national population (0.5% per year). Urban areas with more than 700,000 inhabitants are growing faster on average than the national average (between 0.5% and more than 1%). These areas account for 20% of the French population and 38% of the national population growth. Between 200,000 and 700,000 inhabitants, urban areas grow at an average of 0.4%. Bellow 50,000, the average is 0.1% (INSEE, 2021).

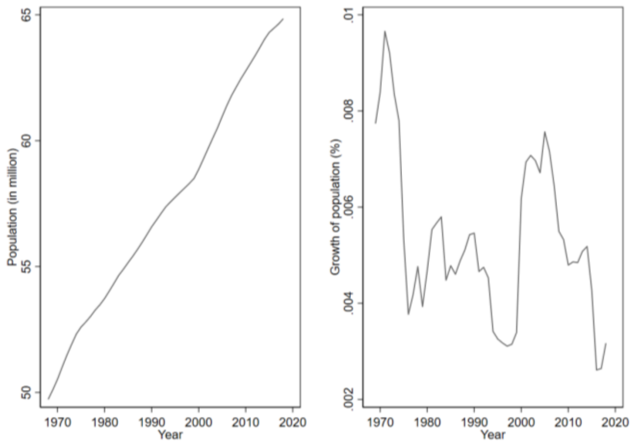


Figure 2 : Evolution of Metropolitan French population between 1968 and 2018. Source : INSEE.

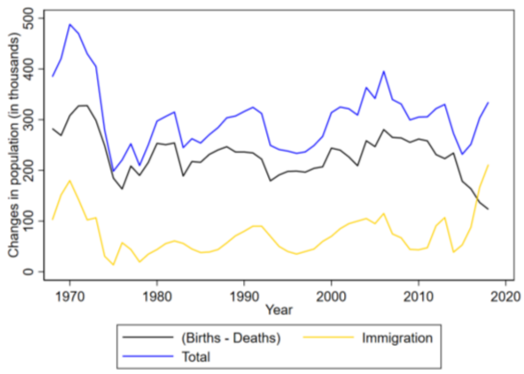


Figure 3 : Details of changes in Metropolitan French population from 1968 to 2018. Source : INSEE.

c) Number of cars per household

The 1970s saw the emergence of peri-urbanization, with the advent of suburban areas, shopping centers outside cities, and building of new roads. This model has been perpetuated over time thanks to the increasing car's accessibility for households and the lack of alternatives (Laugier, 2012). Moreover, figure 4 shows that there is a slight but consistent increase of cars per household in France over the period 2006-2018.[4] In recent years, this model has been called into question, particularly because of the ecological impacts it induces.

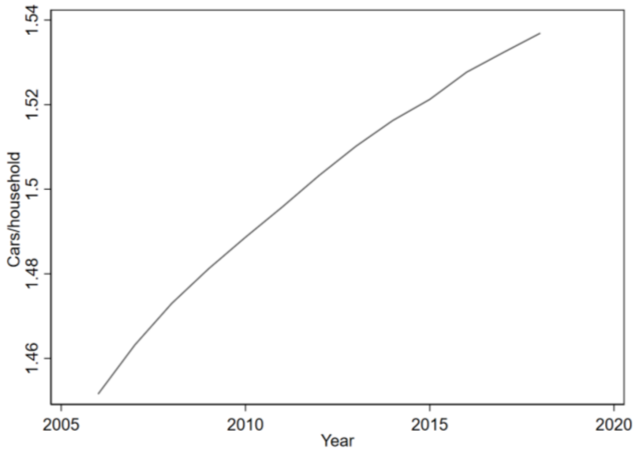


Figure 4 : Average number of cars per household in France between 2006 and 2018. Source : INSEE.

[4] We have drawn the curve for the period 2006/2018 which corresponds to the period of our sample which allows us to establish a trend, despite the absence of data for previous years.

II) Literature

In this chapter, we will review the relevant literature to gain insights into the likely effects of Fare-Free Public Transportation as well as, more generally, public transport and infrastructure investments. The latter is included since FFPT can be viewed as one form of (public good) infrastructure investment, and because studies analysing the impact of infrastructure investments tend to use the type of empirical approaches that will also be relevant for our own analysis.

1) Fare-Free Public Transportation

a) Change in public transit prices impacts networks management and consumers behaviour

We would think that a downward change in prices could be fatal to the network. However, the ticketing revenues are for many networks limited. This financial loss can be more than outweigh by the efficiency gain, the cost savings of the fare collection and control infrastructure, and the convenience to the driver of not having to control users (Hodge et al., 1994). Due to the higher patronage, this effect can be counterbalanced by the lower level of services or the necessity to invest much more to keep the same level of comfortability (Storchmann, 2003). Nevertheless, most cities that switch to free transport report that services are underused. For example, some city mayor said they wanted to "carry passengers rather than empty seats" in France (Contard, 2019).

The effects of changes in transit fares have been widely studied in the literature. One of the fundamental questions is whether Public Transportation should come at the right price, or whether it should be a public good that maximizes welfare (Cervero, 1990; Contard, 2019). Many researchers have discussed optimal pricing for public transport. The Simpson-Curtin Rule, which is extensively discussed in most sources, states that a 10% price reduction results in a 3% increase in ridership (Curtin, 1968). This result must be qualified, however, and obviously depends on the period (peak or off-peak), the location, the quality of service provided, or the user profile (Cervero, 1990; Hodge et al., 1994). Still, free transport could lead to a higher use of public transport through a strong price signal.

Optimal prices cannot be thought of without considering other means of transportation. Especially, the cost of the car is greatly undervalued compared to the externalities and costs it imposes on society (Storchmann, 2003). Thus, to obtain much bigger effects on modal shift, it would be necessary to either pay the user to take the bus, or combine FFPT with an increase of the cars' cost by putting tolls at the entrance to cities, a rise of the parking lots prices, or by increasing the attractiveness of public transport by increasing the quality and the frequency of service, and by extending the networks (Cervero, 1990; Kipfer, 2012).

b) Details of potential modal shifts induced by FFPT

A modal shift is defined as the modification of the market shares of the different modes of transport between them. Ideally, the authorities would the price signal involved by FFPT lead car users to move toward public transportation infrastructures.

In the main European cases studied, Hasselt and Templin show a strong increase in ridership, but with a limited effect on modal shift from car to public transport (Fearnley, 2013; Storchmann, 2003). Therefore, they detected undesirable effect of attracting people who used to travel by soft transport means (cycling, walking, etc.), and for shorter trips that they could have made by these same means of transport. They also discovered a phenomenon previously documented and consisting of unnecessary trips by young people who take the bus much more than they need to.

However, Aubagne and Dunkirk, two other well documented European cases, see rather positive results (Cats et al., 2012; Huré & Javary, 2020). Even though congestion and modal shift is limited, 5% of the study respondent declared that they didn't buy a car following the implementation of FFPT in Dunkirk, meaning that the policy might work (Huré & Javary, 2020). All these figures must be qualified. Indeed, they are the result of qualitative surveys that sometimes lack the necessary precision to allow for an accurate translation of these figures (Dricot et al., 2019).

c) FFPT can be socially desirable

Many of the proponents of this measure believe that it could have a very significant effect in opening up fragile populations (Cats et al., 2012; Contard, 2019; Cordier, 2007). This idea seems to be consistent with the spatial mismatch hypothesis, which has been studied extensively in the economics and transport literature and was first mentioned by (Kain, 1968). In his paper, he demonstrated that in the United States, blacks who were segregated away from employment areas had much more difficulties finding a job than the rest of the population. More generally, the most disadvantaged populations are often ostracized : the real estate prices are more expensive next to activity areas. As a result, the most disadvantaged people must live far from places of employment, buy and maintain a car when they can afford it, or use public transportation. They are far from employment, both physically and by transportation time. The time cost (distance, congestion, etc.) and monetary cost can be a barrier to employment (Blumenberg & Manville, 2004; Gobillon & Selod, 2021).

FFPT, which removes the monetary psychological barrier, allows everyone to move around as they wish in the areas concerned. For the poorest part of the population, even a decrease in price of cents of euros could have positive effect. The hypothesis is that FFPT acts on its accessibility by reducing the psychological barrier of cost that it induces when it comes to paying a ticket, or to doing the administrative steps to access the reduced fares (cost of time and money). In fact, although we are in the digital age, it is also often necessary to travel to canvass companies, find the right job openings, get an interview, train, and improve the worker skills. High transportation costs can prevent this process (Gobillon & Selod, 2021). Thus, by breaking down this barrier, they may be more mobile and more exposed to the job offers. Therefore, Tallinn had made it a clear objective to enable its residents to travel to look for a job (Cats et al., 2012). This can also increase the mobility of students, who can engage in culture, socializing, and schooling, and senior citizens, which can have significant economic effects for the local economy (Cats et al., 2012). Some hypothesize that paying for a ticket, whether at full fare or even if it is at a highly discounted fare, can greatly reduce people's willingness to use public transport, by the psychological cost it induces (Contard, 2019; Hodge et al., 1994; Huré & Javary, 2020).

d) FFPT has other unexpected effects

Other unexpected effects have been observed. In Templin for instance, the number of accident with pedestrians and cyclists has been decreasing. The reason is that those individuals are giving up these modes of transport in favour of the bus (Storchmann, 2003).

Vandalism and incivilities increased in some cities (Baum, 1973; Hodge et al., 1994). This last argument has been denied in many cases and seems to be function of factors such as the quality of services, the crowdedness, and the type of transport (Delavoye et al., 2022). In a general manner, the explosion in ridership involved by FFPT indicates that it is not advisable for cities whose public transport systems are already saturated to switch to this policy of free travel, which could significantly degrade the quality of services (Contard, 2019; David, 2021), restricting this measure to cities with significant room for maneuver.

Despite the strong public interest in FFPT and the controversies associate with the topic, this public policy has been little studied, and the literature is therefore limited. Although some case studies have been done, debates for or against are often the result of personal opinions or observations (*Certu*, 2010) rather than the foundation of results obtained empirically through a scientific process. Furthermore, there is a lack of standardized research methodology for this specific subject (Grzelec & Jagiełło, 2020).

2) Transport infrastructure's impacts

Thereafter, we will identify how researchers has tried to assess transport improvements impacts until now. This section will outline the main lines of research studied to date, the variables studied and the econometric methods used, which will allow us to start preparing the methodological discussion.

a) Transportation infrastructures tend to influence real estate prices (hedonic prices)

There is a large literature around the impact of local public transportation. As noted by (Yang et al., 2019), the intensity of the treatment depends on the nature of the development. We can expect to spot stronger effects on the creation of a commuter rail, which often connects remote territories in a very efficient way to the spaces of interest (shorter, more comfortable trips), when the communalities buses will surely have a much more limited effect according to the existing research. The results also differ according to the empirical strategy used, the variables observed, the demographics of the area, and the time period studied (Rietveld et al., 2007).

Many researchers have investigated the effect of public transport on property prices using the hedonic pricing method. Among the best-known studies are (Baum-Snow & Kahn, 2000), which demonstrates the role of proximity to new stations on property values and rent increases in the area. (McMillen & McDonald, 2004) suggests that real estate prices increased even before the construction of a Bus Rapid Transit connecting the city to Chicago Midway Airport, demonstrating the value of infrastructure to residents and future residents. (Bowes & Ihlanfeldt, 2001) demonstrates an increase in real estate prices near new train stations in Atlanta. He breaks down the price and shows that crime has a small negative effect on the homes closest to the new facilities.

The hedonic pricing method is a good way to reveal the value that residents attach to these infrastructures. Nevertheless, it requires an extremely large data collection. Moreover, it must ensure that the model is well specified, otherwise the estimator could be biased (Wing & Chin, 2003).

There are, however, other ways of measuring the impact of public transport infrastructure. Thus, scientists have increasingly sought to show the causal effect of public transport infrastructure on economic variables by finding a counterfactual. We explore through part b) the most well-known existing paper in this area, and the outcome variable studied. Then, we will discuss in c) the endogeneity issues arising from the used econometrics technics and how we can deal with it. This last part will ultimately help us understanding the choices that has been done to build the following parts of this thesis.

b) Transportation infrastructures also play a role on micro and macroeconomics variables

From a territorial development perspective, (Banerjee et al., 2012) evaluates Chinese transport development policy in the 1980s. They argue that these have contributed to higher GDP per capita, more firms, and higher profit per firm the closer cities are to new infrastructure. Nevertheless, the differences are small. Thus, researchers question the benefit of the investments at such a high cost. Over a similar evaluation period, (Duranton & Turner, 2012) point to the heavy annual public investment in US roads. They explain that the employment rate rises significantly as the road stock increases. Nevertheless, they suspect that the policy of new road construction is the consequence of a negative population growth shock. Thus, to attract new people to the city, roads are built. This is possibly at the expense of social policies. (Gibbons et al., 2012) measures the impact on the number of businesses, productivity and employment of new roads built in England between 1998 and 2008. Notably, the researchers find a growth in the number of inbound firms that is accompanied by a growth in the employment rate in the affected areas.

Finally, there are few studies of how public transport influences household variables. (Baum-Snow & Kahn, 2000), for example, measures a slight positive causal effect of rail construction, bringing households closer to this type of mobility, on ridership. (Mayer & Trevien, 2015) examine demographic changes around new commuter rail. They show that the population does not increase but that the surrounding areas gentrify, in line with the Tiebout's sorting hypothesis. (*Commissariat Général au Développement Durable*, 2019) also finds a gentrification effect with rising wages around the new Paris metro stations, which open up the areas concerned. (Faulk & Hicks, 2010) is perhaps the work that comes closest to ours. Indeed, by introducing the definition of public transport as a social good, they observe the effects of public transport between small and medium sized cities that have a public transport network and those that do not.[5] They find that the transport network has a positive effect on the reduction of unemployment, on the increase of population growth and employment rate, but also on less common variables such as the reduction of food stamp distribution.

c) Endogeneity discussion

This discussion aims to better understand our methodology choices further away in this thesis. Indeed, the studies in the last paragraph systematically reveal problems of endogeneity. The installation or improvement of transport infrastructures can be directly linked to the territory's economic health.[6]

Like (Banerjee et al., 2012; Mayer & Trevien, 2015), some researchers try to prove that infrastructure are randomly allocated in the concerned area, which does not make the treated population different from the control group, and thus allows the experiment to be carried out. Others clearly face an endogeneity problem (Duranton & Turner, 2012; Gibbons et al., 2012). The explanatory variable is linked with the error term, which bias the OLS estimate. To solve

[5] Even if it is not formally written, many studies such as (Duranton & Turner, 2012) show that transport infrastructures can be seen as social investments or social expenditures.
[6] Discussed more in-depth in the methodology part of this thesis.

this problem, they use an instrumental variable. The main problem of this strategy is that finding a good instrument is difficult. For our experiment, it would mean that we should find a variable that can explain with enough correlation why cities are moving toward free-of-charge network, while not being correlated with our dependent variable. Later in this work, we will see that we have sufficient elements to think that we can follow the random assignment reasoning discussed in the first part of this paragraph.

To sum up, this dissertation is at the crossroads of the literature on the evaluation of the effect of bringing households closer to public transport, and the effect of free transport, which has never been studied by an empirical approach.

III) Theory

This chapter sets out our main theoretical arguments regarding the likely influence of FFPT. Given that our focus will be predominantly on three outcome variables – i.e. unemployment, population growth, and car ownership – we will discuss each of these in turn.

1) Public Transit accessibility and decrease in unemployment

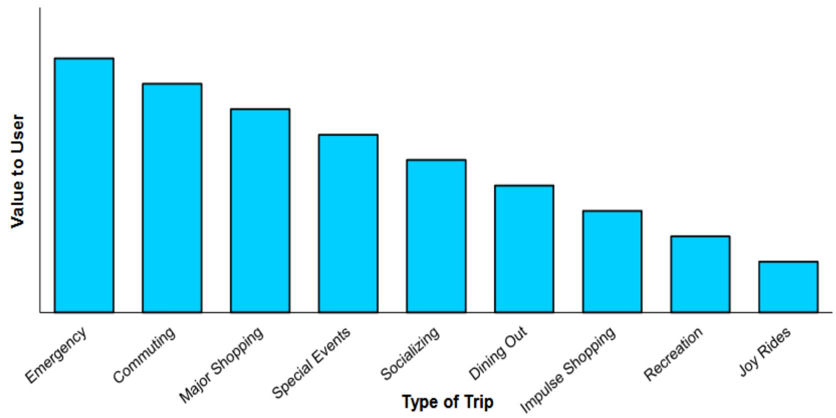
As mentioned previously, Fare-Free Public Transportation can be considered as a downward shock to transport prices from the perspective of the end-user (who now no longer has to pay a user fee). Prices influence the consumption patterns of individuals (depending on their preferences) as reflected in the price elasticity of public transport services. This elasticity, by definition, consists of evaluating the percentage change in the use of the means of transport when the price of the said transport decreases by 1%.

$$Price\ Elasticity = \frac{\Delta D / D}{\Delta P / P}$$

With $\Delta D = D_t - D_{t-1}$ and $\Delta P = P_t - P_{t-1}$, whereby D_t stands for the demand for the good at time t and P_t the price of this good at time t. In theory, when the price of transport falls, its consumption will tend to rise. Yet, how strong this effect is will be regulated by the price elasticity of demand.

Importantly, the price elasticity of demand for public transport services is unlikely to be the same for all groups in the population. One can imagine, for instance, that demand for public transport will be more price-sensitive for poor compared to wealthy people. Wealthy people are likely to have alternative means of transport available to them and therefore have a very low likelihood of responding to price changes in public transport. Poor people, however, have less alternatives and are likely to face a much tighter budget constraint. Hence, small changes in the price of public transport can make a big difference for them. This is important since public transport allows people without easy or regular access to alternative forms of transport to nonetheless attend social activities and find job opportunities. It may also allow them to search for – and maintain – jobs in a wider geographic radius. Hence, particularly among the most socially and economically vulnerable groups in society, reducing the price of public transport can be a considerable help in job search as well as commuting to and from work at a further distance. This, we argue, may cause the unemployment rate in a city to decline when FFPT is implemented.

The line of argument is in part based on (Litman, 2022), who classifies distinct types of transport consumption by order of importance (see figure 1). In his view, when transport is (too) expensive, it will only be used for the most important (emergency) tasks. Once transport becomes cheaper, it can also be used for travel that improves the standard of living (rather than primary needs) – such as special events, dining out or recreation. This argument can easily be applied to public transport, where it is likely to be of most relevance for social groups reliant on public transport for their mobility (such as the socially and economically vulnerable segments of the population). More specifically, if public transport becomes free, the most vulnerable households will be able to travel more and use public transport for more than just emergency situations (see figure 2 : zero fare means virtually an infinity number of trips possible). This is expected to improve their access to social activities and job opportunities (e.g., in case this required commuting to and from work), and thereby may exert downward pressure on unemployment rates (at least among the vulnerable). This is in line with the argument made by Gobillon & Selod (2021) or Delavoye et al. (2022).



Trips range in value. High value trips will occur even if user costs are high. Some trips have relatively low value and will only occur if prices are low.

Figure 1 : Travel ranked by user value. Source : (Litman, 2022).

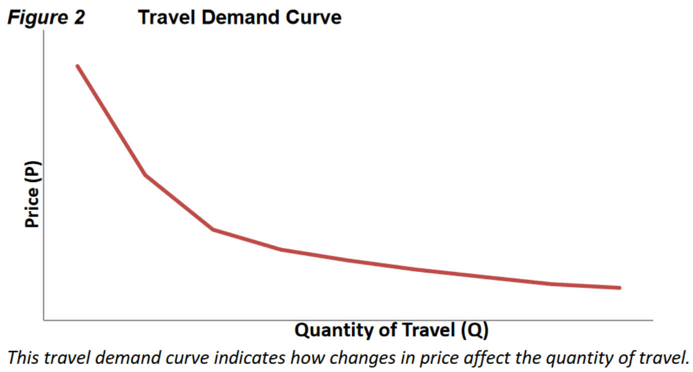


Figure 2 : Travel demand curve. Source : (Litman, 2022).

Hypothesis 1 : By allowing improved access to social activities and job opportunities particularly among the socially and economically vulnerable parts of the population, FFPT transport is expected to reduce unemployment.

2) Territory's attractiveness and population growth

According to (Tiebout, 1956), each city offers a set of public goods that provide a level of utility to its inhabitants and are financed by different tax rates set in correspondence to the supply of the public goods. This set of public goods can be police officers, the creation and maintenance of roads, the construction of schools, the maintenance of green spaces, or the provision of local public transport services. Theoretically, the greater the supply of public goods, the higher the taxation required to fund this supply (all other sources of funding kept equal). Each household locates in a city according to its preferences, creating an equilibrium where each household enjoys an optimal public service.[7] The theory makes several assumptions: that there is full information, that households are fully mobile, and that the costs and benefits of public goods do not spill over from one community to another.

A key insight from Tiebout's theoretical model is that when households see an opportunity to increase their utility by living in another location that offers are 'better' mix of public services, they will attempt to migrate to the city in question: i.e. people vote with their feet. (Banzhaf & Walsh, 2008) offer an interesting example. They use air pollution data, which is arguably largely exogenous to government action. Thus, lower pollution does not imply

[7] As demonstrated by (Banzhaf & Walsh, 2008) among many others, some public goods are not necessarily coming from the government, such as air breathability. The numerical value of the costs and/or benefits of these public goods is likewise taken into account in the inhabitants' location decision in the Tiebout model.

higher taxes, which would rebalance the utility gained by a disutility of a larger fiscal contribution. The study shows that when pollution falls in a given city, the population of that city tends to grow, in line with predictions from the Tiebout sorting hypothesis.

The above line of argument can also be applied to our setting of free versus non-free public transport. Free transport increases access to mobility, which has a certain monetary value for at least certain groups of the population. Making public transport free might furthermore have a non-negligible side-effects that contribute to increasing the value of a given location as a place of residence: e.g., reducing traffic and pollution if car use decreases, reducing health problems of the inhabitants when pollution declines, making the location a safer place to live when the number of accidents declines, etc. The combination of all these effects tends to increase the utility of the people living in the area, which leads to our second hypothesis that FFPT can be expected to spur population growth.

In France, FFPT is largely financed by the "Versement Mobilité" (mobility payment), which is a contribution paid by companies and is a function of total employees' income and the tax rate (Contard, 2019). Therefore, households are not directly paying for FFPT. According to Tiebout's hypothesis and our line of argument above, one can therefore imagine that FFPT creates benefits without additional costs for households. Thus, people will tend to move in those cities.

Hypothesis 2 : "People vote with their feet". By improving transport services, FFPT attracts people to move towards those cities. Thus, population growth should increase faster In FFPT compared to non-FFPT cities.

3) Substitution effect and household cars ownership.

By eliminating the monetary costs involved in buying a daily ticket or a monthly bus pass, public transport mechanically becomes more attractive compared other sources of transport. To see how this affects the use of other means of transport – such as cars – the cross-price elasticity of demand becomes relevant:

$$Cross\ Price\ Elasticity = \frac{\Delta D_C / D_C}{\Delta P_T / P_T}$$

With $\Delta D_C = D_{C,t} - D_{C,t-1}$ and $\Delta P_T = P_{T,t} - P_{T,t-1}$, $D_{C,t}$ being the demand for car ownership at time t and $P_{T,t}$ the price of public transportation at time t.

(Litman, 2022) which identifies and list an extensive number of studies about transport demands and price elasticities, exposes positive cross elasticity between demand for car ownership (or said differently, the stock of cars for households) and price of public transportation. They find slightly positive results, meaning that when price of public transportation decreases, the car ownership tends to decrease as well. The underlying idea is that as public transport becomes free while the cost of car usage remains the same, at least some people are likely to shift from being car user to public transport user because public transport becomes a relatively cheaper option. Note that, in similar vein, people may also shift away from other forms of transport. For instance, when public transport has become as free as walking (while being faster and more comfortable to reach your destination), people are likely to shift from being pedestrian to public transport user (modal shift problematic explained in the literature). This line of argument leads to our third and final hypothesis.

Hypothesis 3 : If cars and public transportation are substitutes, FFPT will lead to a decrease in car use, which will in turn translate into a decrease in car ownership.

IV) Data

In this chapter, we will present the data used on the empirical analysis below. The first section will describe the sources of the data we employ – both when it comes to the operationalization of FFPT and the three main outcome variables (unemployment, population growth and car ownership). Then, the second section will present basic descriptive statistics if these variables in order to familiarize the reader with the data and ease interpretation of the effect sizes in the analysis below.

1) Sources

For our operationalization of FFPT, we take data from the French research and consulting organisation "Innovative Cities and Knowledge Management" (VIGS). They have brought together extensive information about all the public transport networks that have implemented free-fare public transport within their territory. This information includes the date of implementation as well as the number the cities covered by the free-fare transport network. This information is critical to code our treatment variable (i.e. FFPT). Importantly, however, some public transport networks do not concern one city, but cover a group of cities. Hence, we link the VIGS data with the data of the French "Center for Studies and Experience in Risk, Mobility and Urban Planning" (CEREMA). Their dataset provides us with the name of the public transport network, the details of the cities belonging to this network as well as their date of entry into it. We are using the 2017 version of their dataset since this is closest to the census conducted in 2018 (which is the final point of our dataset; see below). Putting both datasets together, we are able to know precisely which city is treated with FFPT, and at which point in time that became the case. Even so, some corrections had to be made. This is the case of Aubagne, for instance, which has recently been linked to the Marseille network, and which appears as such in the CEREMA data. Nonetheless, it still offers free transport to all its inhabitants within the "Pays d'Aubagne et de l'Etoile" agglomeration.

It is important to note that CEREMA gives us the network organisation in 2017, but this does not mean that this reflects the reality throughout our entire observation period (which covers the period from 1968 onwards due to data availability for our outcome variables; see below). For instance, the situation may have been different in the 1960s and 1970s. As a result, it might be the case that some cities where not linked to a transport network at this period whereas our 2017 data state that they (currently) are linked. Although it is impossible to know how much changes have taken place over time (in the absence of detailed historical public transport network data covering the more than five decades since 1968), we do know that such mis-allocations will lead some FFPT-treated cities to be allocated to the control group, and vice versa. Mis-allocations of this kind will therefore tend to introduce noise in our estimations and bias the obtained point estimates towards 0. This will therefore make it more difficult for us to observe statistically significant effects in the empirical analysis.[8]

For our dependent variables, we will use the census data that the French "National Institute of Statistics and Economic Studies" (INSEE) produced for the years 1968, 1975, 1982, 1990, 1999, 2008, 2013, 2018. This data source provides information about the number of unemployed among those in the labor force between the ages of 15 to 64 years old (or between 25 to 54 years old). This allows us to calculate two versions of the unemployment rate for each city at the time of each census. These will be our first dependent variables to assess hypothesis 1.

The census data also include detailed population counts for each city in France, which will allow us to establish the annualized population growth rate of each city. This will be our second dependent variable to assess hypothesis 2.

Finally, to assess the change in households' car ownership, we will analyse the INSEE households' car ownership dataset for the main residence. This is produced every year from 2006 to 2018 based on annual data collection and averaged across a 5-year period. This will be our third dependent variable to assess hypothesis 3.

2) Descriptive statistics

Table 1 gather the descriptive statistics. *Villages 2018* shows the population size in municipalities with less than 2,000 residents, while *Cities 2018* includes those with more than

[8] We should furthermore note that CEREMA dataset does not give us the Paris area network (neither Paris, nor the cities around). While we could have gathered all the cities by hand, we decided not to include them since Paris is arguably not representative for any other city in the French territory.

2,000 residents. This size population separation is important, particularly because we suspect a stronger treatment effect in the more populous cities (more details into the methodology).[9]

FFPT 1968 to *FFPT 2018* are the dummy variables taking 1 when the city transit is free of charge for the users at last the 31st of December of the previous year, and 0 otherwise (said differently, if a city is implementing FFPT in year 1975 such as Compiègne, she will not count as FFPT for this year).

% Unemp1 is the unemployment rate of observed municipalities from 0% (all active population has a job) to 100% (all active population is unemployed) for the 15-64 years old population, while *% Unemp2* is the same setting nevertheless for the 25-54 years old population. We pooled it in 2 periods. Indeed, we consider that the structural unemployment rate is different before and after the oil shocks, as explained in the introduction.

% Pop growth is the average annual growth rate of population during the sample period 1968-2018 for all municipalities.

Finally, # *Cars per household* represents the average cars ownership for the sample and each year between 2006 to 2018.

Note that the number of observations may vary slightly from one year to another. This is due to a punctual lack of data depending on the dataset used. We could have balanced our dataset so that only municipalities with complete information for all variables appear. However, we felt that this was unnecessary, and could lead to a loss of information, thus leading to a loss in the quality of the estimates.

[9] We have arbitrarily chosen 2018. The composition of other years is similar, except few changes in case of missing data or cities jumping from one category to the other (less or more than 2,000 inhabitants), which is rare.

Table 1 :

Descriptive statistics

	Obs	Mean	Std Dev.	Min	Max
Villages 2018 (< 2000 inhab)	6,080	706.7822	500.2337	4	1998
Cities 2018 (>= 2000 inhab)	2,712	10977.57	30224.25	2002	868277
FFPT 1968	8,854	0	0	0	0
FFPT 1975	8,797	0	0	0	0
FFPT 1982	8,834	0.0001	0.0106	0	1
FFPT 1990	8,867	0.0003	0.0184	0	1
FFPT 1999	8,871	0.0005	0.0212	0	1
FFPT 2008	8,788	0.0058	0.0760	0	1
FFPT 2013	8,790	0.0093	0.0961	0	1
FFPT 2018	8,792	0.0164	0.1269	0	1
% Unemp1 1968-1975	17,651	2.1974	3.2972	0	100
% Unemp1 1982-2018	52,942	9.5154	5.2611	0	100
% Unemp2 1968-1975	16,702	1.3993	3.1256	0	100
% Unemp2 1982-2018	50,150	7.8007	5.9769	0	100
% Pop growth	61,174	1.2103	3.3013	-11.11	224.00
# Cars per households	114,226	1.5076	0.2106	0	3

France had 35,228 cities and villages in 2018. Therefore, according to Table 1, our sample gather approximatively one quarter of the full population. Almost one third of those municipalities are cities (>= 2000 inhabitants).

As stated in the introduction, FFPT has been marginal until the 2000s, when it has started to develop at a higher pace. In 2018, FFPT represented 1.64% of cities owning public transit services, thus 144 cities.

At the end of the Glorious Thirties, the average unemployment was of 2.20%, with a standard deviation of 3.30% for the 15-64 years old category. This put a major part of the sample between 0% (unemployment rate cannot be negative) and 5.50%. We can see, however, that there are a few cities that have very low (0%) or very high unemployment rate (100%). We can strongly suspect that these numbers come from small villages, more vulnerable to extreme values. After the oil shock, unemployment is much higher, with a mean of 9.52% and a standard deviation of 5.26%. This confirms the trends mentioned in the introduction at the French level. For the 25-54 age group, unemployment is lower for the two periods, respectively 0.7% for the first, and 1.7% for the second. The minimum (0%) and maximum (100%) probably come from small villages as well.

Population growth per city through years has been of 1.21% on average with a standard deviation of 3.30%. We have some extreme values going from -11.11% to 224% for one year.

This could be explain by special events (for instance, there has been a few merging cities, that could artificially increase the population) or small cities that are very vulnerables to population changes.

Eventually, between 2006 and 2018, the average number of cars per household has been 1.50 (thus, between 1 and 2 cars). The standard deviation is tight (0.2106). The minimum is 0 car per household, maximum is 3, “3 or more” being the last option of the survey. It means that the mean cars per household might be underestimated if some own 4 or more.

V) Methodology

In this paragraph, we will first introduce the econometric model that we will use, the staggered DiD. It will allow us to obtain the causal effect of free public transport on our variables of interest. This requires checking some hypotheses. Thus, in the following paragraphs, we will perform T-tests (to see if the treatment and control groups are similar before the treatment), and we will argue on the exogeneity of the explanatory variables. In a second step, we will discuss the accuracy of the treatment of our study, before defining the scope of our treatment (study period, type of FFPT selected as the treated group).

1) Empirical approach

Fare-Free Public Transportation is a unique shock to the public transport network in a given area, going from costly toward free-of-charge for the users. Since not all municipalities have made the move towards FFPT in France, there are some public transport networks with FFPT and some without. This constitutes a fruitful setting for using a Staggered Difference-in-Differences (DiD) approach to estimate the causal effect of FFPT on our variables of interest. Stated differently, we can use the cities without FFPT as a 'control group' for the cities with FFPT in the 'treatment group'. The former thus provide an assessment of what would have been the outcome variable of interest in case FFPT would not have been implemented (which is valid under certain assumptions we will return to below). We will adopt a regression similar to (Faulk & Hicks, 2010).

$$Y_{i,t} = \varphi_t + \alpha_i + \beta FFPT_{i,t-1} + \varepsilon_{i,t}$$

Y_{it} represents our respective dependent variables, namely unemployment, population growth, and car ownership. $FFPT_{i,t-1}$ is a dummy variable taking the value 1 once the city is treated, with a lag of one period. It means that if we are evaluating the unemployment rate in city X in 2014, we will link that to its FFPT in the year 2013. The lag's reason arises from the fact that we judge that the treated cities cannot observe changes at the very beginning of the implementation, because it takes some time for FFPT to start having social, economic and environmental effects. β is our coefficient of interest, and represents the average treatment effect on the treated cities. φ_t is the year fixed effect. It enables us to estimate a different intercept from year to year, which accounts for common temporal effects such as the economy and the society evolutions. α_i is the city fixed effect. This term is catching all unobserved time-invariant characteristics of a city that could be correlated with the explanatory variable – such as its history or culture.

It is important to observe at this point that we are pooling cities with different treatment dates in our analysis. In practice, that implies that we have staggered introduction of FFPT. In recent years, it has been argued that this may cause bias in difference-in-differences estimators of the type we use here (Baker et al., 2022; Goodman-Bacon, 2021). One reason is that there may be heterogeneity over time in the effect of FFPT (i.e., introducing it in 1971 is not the same as introducing it in 2012). Another reason is that municipalities in the control group for early innovators may become treated units in later years, which may make them an inappropriate comparison group for the early adopters (or, at least, different from municipalities that never introduce FFPT). In our setting, we do not take these potential difficulties into account, mainly because there are only 144 cities or villages adopting FFPT in France in our time period (1.64% of our sample). Most of the control group thus by construction is a never-adopter. We assume that this mitigates any problem with staggered introduction of FFPT (though we of course acknowledge that future research should assess the validity of this assumption in detail!).[10]

To represent the causal effect of change in our explanatory variable, the DiD estimate needs to control for pre-treatment trends. For instance, let's take the unemployment variable and imagine that before the treatment the unemployment rate is decreasing in future FFPT cities, while it is increasing in the control group. If the average treatment effect is observed to be negative, it could then be that this is more the result of these diverging temporal dynamics rather than because of the introduction of FFPT itself. This would lead to biased estimates and inferences. Hence, it is important to verify that cities in the treatment and controls groups are similar – and on similar trajectories – before the treatment (common trends assumption).

To test this hypothesis, we have run a series of T-tests, comparing the average of each variable in each year, between the control group and the treatment group, before the

[10] For more details, (Goodman-Bacon, 2021) decomposes the staggered estimate. He shows that what is likely to bias the estimate is the inclusion into the computation of early treated units as control group to compare with the new treated units. As it is a sum of weighted averages, and we have a huge never treated group, we consider that it will only influence very slightly our estimate. The same apply for the treatment heterogeneity discussion.

treatment.[11] If we cannot reject the null hypothesis stating that the 2 means are different, then we consider that treatment and control group are similar before treatment. You can find the T-tests tables at the end of the methodology part (Table 2 to 5). The results suggest, except a few cases that are highlight in clear blue (namely car per households between 2013 and 2018), that treatment and control groups are similar prior to treatment.[12] This strongly suggests that any differences arising after implementation of FFPT are due to this changes in the price of public transport (rather than pre-existing differences between the groups of municipalities).

A fundamental assumption of an Ordinary Least Square model is the strict exogeneity of the explanatory variables. As highlighted in (Faulk & Hicks, 2010), our explanatory and explained variables might simultaneously affect each other. More precisely, the FFPT decision might be influenced by the economic situation, the environmental situation, or negative developments in terms of population. For example, we could imagine that FFPT is costly and implemented only in cities that have a strong and dynamic economy with low unemployment. On the other side, FFPT could according to our hypothesis help to revitalize city centre and increase the mobility of vulnerable households, and therefore reduce unemployment. Then FFPT explains unemployment, and unemployment could explain FFPT, leading to the simultaneity equation bias. While not a perfect solution to the simultaneity issue (given that there is likely to be some persistence in economic, demographic and environmental variables over time), we address this concern to some extent by using the lagged value of FFPT in our estimations. It would be hard to argue that unemployment today influences the introduction of FFPT last year, while it would be more natural that FFPT introduced last year affect unemployment today.

Finally, assignment to the treatment should be exogenous for the validity of DiD estimates. From this perspective, we are advocating that cities that are treated are 'as-good-as' randomly selected since we are not aware of any precise characteristics for the transition from non-free to free-of-charge public transport system. Cities of varying sizes are taking the plunge, all over France, regardless of the mayor's political label (this political decision could be associate with left wing parties for instance) (Contard, 2019). Some might also argue that only small and medium-sized cities decide to adopt this measure. As (Delavoye et al., 2022) points out,

[11] To avoid any misunderstanding, # *Future treated group* represents the future treated cities. We have 144 cities treated cities in 2018, and 144 future treated cities in 1965 with the 2018 available information. Therefore, this number drops when year goes by.

[12] Treatment and control groups are considered as non-similar when t-test have p-value < 5%.

this is not true, as Luxembourg has adopted free transport for all its inhabitants, as has the capital of Estonia. Finally, Montpellier agglomeration (<450,000 inhabitants), is also moving to free public transports from 2023. It will become the largest city in France to apply this measure. Furthermore, the T-tests documented previously confirm that the unemployment rate, growth of population, and car ownership are similar between the treated and control groups (before the implementation of FFPT). Thus, we believe that the pool of cities treated is, by virtue of its diversity and similarity to non-treated cities, not selected based on values of the outcome variables of interest to us. The only barrier to free transport thus seems to be its ability to absorb the growth in passenger inflow generated, which does not affect the consistency of our estimator.

2) Discussion on treatment accuracy

Throughout the existing academic literature, researchers have used different units of analysis to estimate the effect of infrastructure developments or shifts in the public transport modality. For instance, (Mayer & Trevien, 2015) is trying to assess the impact of new commuter infrastructure in Paris and its vicinity by defining the treatment variable at the city scale. This corresponds to our approach. That is, we look at cities within a transportation network and compare those that are free-of-charge against the others. On the other side, papers such as (*Commissariat général au développement durable*, 2019) assess the treatment at the level of new transportation infrastructures, such as the metro or bus station scale. In the latter paper, the researchers show that depending on the distance between the transport infrastructure and the inhabitant's home, the effect of the treatment is more or less important. Indeed, one can imagine that someone living near a new infrastructure that positively improves his travel quality (time, comfort, ease of use), will be likely to use it much more than someone thousands of meters away from this infrastructure. Because our treatment is at the city level (and not, say, the neighbourhood level), we will not be able to capture the treatment with as much finesse. This is likely to make us underestimate the effect of our treatment.

Also, we study the local public transport networks without distinguishing their specificities. Thus, for instance, Aubagne (which offers a high level of service to its citizens) will be evaluated in the same way as a small city that offers only one line and about five buses per day. Again, this may lead us to underestimate the effect of the treatment for those who are able to provide high level of services, while overestimating the effect for the others. It is therefore important to keep in mind during our results discussion that we are estimating an average treatment effect. We will partly overcome this issue by considering only cities (more than 2,000 inhabitants) in the robustness checks of our results discussion.

In addition, the evaluation of the variation in our variables of interest could be affected by two other phenomena. The first one is that France already adopts advantageous pricing for young people, seniors, low-income earners, and the unemployed (Contard, 2019). This is often not used by all those have a right to do, possibly because it sometimes is very bureaucratic, because citizens are not aware of their rights, or because they are ashamed to use it (Huré & Javary, 2020). Nonetheless, a portion of this population already uses this access facility. In other terms, while we are stating in our experiment that we are going from public transport where you need to pay, to public transport services free-to-charge, the reality is that some people are already profiting of Fare-Free (or very low fare) schemes. This may reduce our average treatment effect.

Finally, cities that implement free transport for environmental and congestion reasons sometimes do so along with other measures to make car use more costly (e.g., reduction of parking spaces, increase in parking prices, tolls at city entrances) or to increase the level of public transport services (e.g., new lines, new infrastructure improving user comfort, increase in service level). This will constitute a compound treatment, and our data unfortunately do not allow us to separate out the potential effects from such additional measures. This may have a positive effect on our estimated coefficients, especially where it concerns car ownership.

3) Clarification on the treatment choice

Because our census data ends in 2018, the cities in our treatment group in the experiment will be those where full FFPT was implemented before 2018. This eliminates a significant number of agglomerations or cities, such as Dunkirk (implemented in 2018, 200,000 inhabitants) or Calais (implemented in 2020, 100,000 inhabitants). Furthermore, we also eliminate cities where free public transport was implemented at the creation of the network, as it does not allow to capture the change between before and after free public transport.

We have chosen to take all cities that offer fully free public transit, as long as they provide this service at least during the week, and independently of the transport frequency. Thus, some small cities that offering only a few trips per day and with small shuttles are still present in our sample. The reason for this choice is that we believe that this service, however small, can have a positive impact on the mobility needs of the most vulnerable. They can thus travel to get training, to go to work, to find job offers. During the robustness checks, we will validate this hypothesis by excluding the smallest French municipalities from the sample (which are likely to offer only minimal public transport services even when they are free). We do not consider any form of partial free travel (during "off-peak" times, on weekends, for specific groups of people, etc.).

Table 2 :

T-test on the difference in unemployment mean (15 to 64 years old) between treatment and control group, ***during pre-treatment periods*** *from 1968 to 2013.*

	1968	1975	1982	1990	1999	2008	2013
Unemployment (%) control group	1.443	2.954	7.736	9.553	10.418	8.691	10.341
	(0.028)	(0.040)	(0 .060)	(6.071)	(0.063)	(4.079)	(0.049)
Unemployment (%) treated group	1.571	2.986	7.376	9.588	10.235	8.641	9.352
	(0 .145)	(0.219)	(0 .251)	(0.348)	(4.386)	(3.574)	(0.458)
T-test (p-value)	0.387	0.885	0.165	0.920	0.627	0.895	0.035
# Control group	8,710	8,655	8,691	8,723	8,727	8,644	8,646
# Future treated group	144	142	142	141	140	93	62

Note: We are comparing unemployment (15 to 64 years old) in percentage point between the control group (1st raw) and the treated group (2nd raw) before the treatment in each period between 1968 to 2013. Once members of the "future treated group" are assigned the treatment, they move into the treated category. Therefore # *Future treated group* is decreasing over time. The p-value gives us the result of Ha: diff != 0. With a p-value > 5%, we cannot reject the null hypothesis that mean treatment and control group are the same. When p-value < 5%, column is blue coloured. Standard deviation in parenthesis.

Table 3 :

T-test on the difference in unemployment mean (25 to 54 years old) between treatment and control group, ***during pre-treatment periods*** *from 1968 to 2013.*

	1968	1975	1982	1990	1999	2008	2013
Unemployment (%) control group	1.021	1.774	4.858	7.942	9.061	7.317	8.689
	(2.743)	(3.451)	(4.944)	(6.006)	(5.869)	(5.333)	(5.925)
Unemployment (%) traited group	1.221	1.879	4.541	7.778	8.884	7.550	7.759
	(1.927)	(2.236)	(2.945)	(3.986)	(4.961)	(4.289)	(4.553)
T-test	0.240	0.596	0.229	0.645	0.690	0.621	0.142
# Control group	8,228	8,208	8,224	8,238	8,242	8,243	8,234
# Future treated group	133	133	132	130	129	85	54

Note: We are comparing unemployment (25 to 54 years old) in percentage point between the control group (1st raw) and the treated group (2nd raw) before the treatment in each period between 1968 to 2013. Once members of the "future treated group" are assigned the treatment, they move into the treated category. Therefore # *Future treated group* is decreasing over time. The p-value gives us the result of Ha: diff != 0. With a p-value > 5%, we cannot reject the null hypothesis that mean treatment and control group are the same. When p-value < 5%, column is blue coloured. Standard deviation in parenthesis.

Table 4 :

*T-test on the growth of population between treatment and control group, **during pre-treatment periods** from 1968 to 2013.*

	1975	1982	1990	1999	2008	2013
Growth pop (%) control group	1.533	1.990	1.390	0.713	1.160	0.878
	(4.810)	(3.720)	(2.688)	(2.009)	(1.545)	(1.850)
Growth pop (%) traited group	1.845	2.529	1.397	0.719	1.334	1.026
	(3.526)	(3.626)	(1.842)	(1.271)	(1.147)	(1.684)
T-test	0.300	0.082	0.271	0.967	0.141	0.500
# Control group	8,598	8,598	8,598	8,598	8,596	8,596
# Future treated group	142	141	139	138	92	61

Note: We are comparing growth of population in percentage point between the control group (1st raw) and the treated group (2nd raw) before the treatment in each period between 1968 to 2013. Once members of the "future treated group" are assigned the treatment, they move into the treated category. Therefore *# Future treated group* is decreasing over time. The p-value gives us the result of Ha: diff != 0. With a p-value > 5%, we cannot reject the null hypothesis that mean treatment and control group are the same. When p-value < 5%, column is blue coloured. Standard deviation in parenthesis.

Table 5 :

*T-test on number of cars per household between treatment and control group, **during pre-treatment periods** from 2006 to 2017.*

	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Car ownership control group	1.472	1.480	1.488	1.494	1.499	1.505	1.511	1.515	1.520	1.523	1.528	1.531
	(0.209)	(0.209)	(0.208)	(0.208)	(0.207)	(0.207)	(0.209)	(0.209)	(0.209)	(0.211)	(0.211)	(0.212)
Car ownership traited group	1.487	1.498	1.502	1.509	1.515	1.537	1.548	1.569	1.587	1.579	1.577	1.592
	(0.209)	(0.211)	(0.205)	(0.210)	(0.197)	(0.190)	(0.174)	(0.212)	(0.193)	(0.164)	(0.167)	(0.171)
T-test	0.495	0.417	0.517	0.529	0.521	0.186	0.105	0.049	0.010	0.025	0.049	0.019
# Control group	8,643	8,643	8,643	8,643	8,643	8,643	8,643	8,642	8,642	8,642	8,642	8,642
# Future treated group	96	94	93	78	65	64	62	62	60	47	47	47

Note: We are comparing car ownership in number of cars per household between the control group (1st raw) and the treated group (2nd raw) before the treatment between 2006 to 2017. Once members of the "future treated group" are assigned the treatment, they move into the treated category. Therefore *# Future treated group* is decreasing over time. The p-value gives us the result of Ha: diff != 0. With a p-value > 5%, we cannot reject the null hypothesis that mean treatment and control group are the same. When p-value < 5%, column is blue coloured. Standard deviation in parenthesis.

VI) Results and discussion

This chapter summarizes and discusses the main results of our empirical analysis. Given that we study three distinct outcome variables – i.e. unemployment population growth, and car ownership – these will be presented in turn. We will, however, always try to connect the various findings to each other as well as to the theoretical arguments presented in chapter 3 above.

1) Unemployment

When looking at the impact of FFPT on unemployment, we will evaluate the unemployment rate of both 15-64 and 25-54-years old categories. The main purpose of comparing these two groups is that the 15-64 population includes two important components of the most economically vulnerable population groups in terms of unemployment that are not included in the 25-54 years old sample: namely, youth and elderly. As such, we would expect that the FFPT's effect on unemployment would be stronger when analysing the 15-64 part of the population. Said differently, FFPT is expected to have a higher impact on those populations.

a) From 15 to 64 years old

The results are brought together in Table 6, which reports on six different specifications of our baseline regression model discussed above. In column 1, we include the entire dataset of all 8,883 French municipalities. Still, as mentioned above, one could argue that FFPT may not make much difference in very small localities with extremely minimal public transport services. Hence, in column 2, we exclude all municipalities with a population below 2,000 inhabitants. This focuses on just under 2,800 French municipalities, and is to be considered as our main specification. The remaining columns in Table 1 check the robustness of our results to several other sample restrictions. In column 3, we restrict the time period under analysis to 2008-2018, which is the period where most FFPT implementations took place. Column 4 combines both sample restrictions by looking at the 2008-2018 period for municipalities above 2,000 inhabitants. Column 5 then furthermore excludes the largest French municipalities by setting the upper population limit to the largest FFPT city (as of 2018). This intends to make the control group more similar to the treatment group in terms of population size. Finally, column 6 restricts the treatment group to those municipalities that had FFPT for at least five year by 2018. This intends to give an indication of likely longer-term effects of FFPT, which are not directly captured in the rest of the results in Table 6. In all cases, we report the point estimate with associated p-value in parentheses.

Table 6 :

15 to 64 years old unemployment rate changes following the FFPT implementation.

	1	2	3	4	5	6
Treated	-0.0527	-0.440*	-0.326	-0.405	-0.395	-0.537*
	(0.851)	(0.0958)	(0.258)	(0.126)	(0.138)	(0.0515)
1975.year	1.506***	2.076***				
	(0)	(0)				
1982.year	6.277***	7.919***				
	(0)	(0)				
1990.year	8.104***	10.71***				
	(0)	(0)				
1999.year	8.964***	11.91***				
	(0)	(0)				
2008.year	7.232***	10.09***				
	(0)	(0)				
2013.year	8.886***	12.25***	1.654***	2.158***	2.142***	2.159***
	(0)	(0)	(0)	(0)	(0)	(0)
2018.year	8.913***	12.27***	1.683***	2.177***	2.164***	2.178***
	(0)	(0)	(0)	(0)	(0)	(0)
Constant	1.451***	0.818***	8.689***	10.42***	10.32***	10.42***
	(0)	(0)	(0)	(0)	(0)	(0)
Observations	70,593	17,877	26,370	7,854	7,703	7,845
R-squared	0.450	0.754	0.153	0.459	0.453	0.459
# cities	8,883	2,785	8,792	2,737	2,689	2,734

Note: The dependent variable is the unemployment rate among those between 15 and 64 years. The main variable of interest is *Treated*, which equals 1 for cities with FFPT and 0 otherwise. Column 1 considers all the data. Column 2 restricts the dataset, taking into account only cities (communalities > 2,000 inhabitants). Column 3 is reducing the period only from 2008 to 2018. Column 4 adopts both restriction of Column 2 and 3. Column 5 is going from year 2008 to 2018 and restricts the population from 2,000 to the biggest population of FFPT cities in 2018. Column 6 is going from year 2008 to 2018, and is taking as treated only cities with FFPT before 2013. p-value in parentheses ; *** p<0.01, ** p<0.05, * p<0.1

The top row in Table 6 presents the Average Treatment Effect of FFPT on unemployment among 15–64-year-olds. Considering the complete dataset including all French cities (see column 1), we find that moving to FFPT results on average in a reduction of the unemployment rate of -0.0527 (compared to municipalities that do not introduce FFPT). This is a very minimal effect, but, as mentioned, this may be due to the fact that many French municipalities are very small. Hence, FFPT may not have a large effect there since public transport service provision is minimal to begin with. Making a minimal service free will obviously not have a large effect.

Column 2 confirms this line of argument. Once the smaller French municipalities are excluded, we find that moving to FFPT on average lowers the unemployment rate with -0.440 (compared to municipalities that do not introduce FFPT). This is a substantial effect given that the French unemployment rate among people aged 15 years or older historically lies between 7 and 10 % (https://www.insee.fr/en/statistiques/6445457) in the recent years. This finding is confirmed in the other columns in Table 6 where we restrict the sample to cities above 2,000 inhabitants (columns 4, 5 and 6). In each case, the effect size hovers between -0.395 to -0.537 percentage points less unemployment for cities that have implemented FFPT, and the p-value remains close to 10% (or below). This suggests that independently of the exact setting and sample restrictions imposed, FFPT tends to push down unemployment for cities that are more populated – in line with our hypothesis in the theoretical section of this thesis.

Interestingly, when we focus on cities that have implemented FFPT for at least five years in column 6, we find that the average unemployment rate is 0.537% reduced by the implementation of FFPT. This is the largest point estimate observed in Table 6, and also has a p-value very close to the threshold at 5% (making it the most reliable estimate from a statistical perspective). This appears to indicate that FFPT's full effect may be seen only after several years, which advocates for a sufficiently long treatment period time.

While Table 6 gives us numbers directly interpretable in terms of shifts in unemployment levels, we can feel disconformable to interpret some of them. For example, in the 2nd column, free transit has on average led to a reduction of -0.440% in unemployment. In 1965, unemployment rate was 0.818%. Thus, we would have interpreted it such that FFPT has led to -53.79% unemployment rate points, which is pretty unrealistic. The ATE is greatly influenced by the most recent years of the sample, which suffer from higher unemployment rates.

For the sake of completeness, we decided to regress the log of unemployment rate (Table 7), which gives us percentage changes when the public transit network goes to FFPT.[13]

[13] Our dependent variable is log(unemployment+1). We proceeded to this transformation such that cities that have null unemployment are still part of the sample.

Table 7 :

15 to 64 years old unemployment rate percentage changes following the FFPT implementation.

	1	2	3	4	5	6
Treated	-0.106***	-0.0376	-0.0398	-0.0384*	-0.0387*	-0.0480**
	(0.00841)	(0.117)	(0.212)	(0.0711)	(0.0710)	(0.0299)
Observations	70,593	17,877	26,370	7,854	7,703	7,845
R-squared	0.586	0.864	0.132	0.470	0.467	0.470
# cities	8,883	2,785	8,792	2,737	2,689	2,734

Note: The dependent variable is the log(unemployment+1) rate among those between 15 and 64 years. The main variable of interest is *Treated*, which equals 1 for cities with FFPT and 0 otherwise. Column 1 considers all the data. Column 2 restricts the dataset, taking into account only cities (communalities > 2,000 inhabitants). Column 3 is reducing the period only from 2008 to 2018. Column 4 adopts both restriction of Column 2 and 3. Column 5 is going from year 2008 to 2018 and restricts the population from 2,000 to the biggest population of FFPT cities in 2018. Column 6 is going from year 2008 to 2018, and is taking as treated only cities with FFPT before 2013. p-value in parentheses ; *** p<0.01, ** p<0.05, * p<0.1

The top row in Table 7 presents the Average Treatment Effect of FFPT on unemployment among 15–64-year-olds. For column 1, cities that have implemented FFPT see a drop of -10.6% in their unemployment rate. Like Table 6, the estimators are all negative, similar in magnitude, and can now be interpreted for all years, including those with low unemployment compared to today's rates.

The sample without any restriction gives us the strongest and most robust estimates, with unemployment falling by -10.6% thanks to the FFPT policy. Then, and independently of the restrictions applied, the policy reduces unemployment of 15-64 year olds on average between -3.76% (2nd column, which is including only communalities of more than 2,000 inhabitants for all years) and -4.80% (6th column, which is taking only taking cities which have more than 2000 inhabitants and are treated for more than 5 years).

Comparing columns 3, 4, 5, and 6, which represent observations from the years when the policy took off (as a reminder, in France, in the end-2000s), we find that, roughly speaking, free public transport reduces unemployment by just under 4%. The estimate tends to become more consistent when villages are excluded (p-value = 0.071). Finally, when the treatment duration is longer than 5 years, unemployment decreases in the treated cities by an average of -4.80% (i.e. almost 1% more than when all cities are taken into account, including the more recently treated cities). This tends to confirm the hypothesis that the treatment effect is not fully felt in the first years. There may be many reasons for this: citizens may not have known from the start that this new public transport offer existed. They may also be reluctant to change their transport habits at first, before switching. Another possibility could be that municipalities implementing FFPT are attracting workers and gentrify (we will partially rule out this hypothesis in the population growth part of this chapter). In any case, this policy seems to largely benefit the cities that implement it with a significant drop in unemployment that tends to be confirmed and increased as the years go by.

b) From 25 to 54 years old

The results for the unemployment rate among 25-54 year olds are brought together in Table 8. This table takes the exact same form as Table 6, and thus reports on the same six regression specifications for ease of comparison. Note that the number of observations and cities are not exactly the same as Table 6. This is due to data availability. The characteristics of the cities' pool in Table 6 and 8 are nevertheless similar.

Table 8 :

25 to 54 years old unemployment rate changes following the FFPT implementation.

	1	2	3	4	5	6
Treated	-0.423	-0.677**	-1.016	-0.567	-0.559	-0.660
	(0.228)	(0.0200)	(0.118)	(0.166)	(0.176)	(0.118)
1975.year	0.752***	1.283***				
	(0)	(0)				
1982.year	3.828***	5.081***				
	(0)	(0)				
1990.year	6.917***	9.279***				
	(0)	(0)				
1999.year	8.031***	10.83***				
	(0)	(0)				
2008.year	6.291***	9.121***				
	(0)	(0)				
2013.year	7.664***	10.97***	1.379***	1.842***	1.831***	1.843***
	(0)	(0)	(0)	(0)	(0)	(0)
2018.year	7.934***	11.32***	1.643***	2.195***	2.185***	2.195***
	(0)	(0)	(0)	(0)	(0)	(0)
Constant	1.026***	0.323***	7.323***	8.987***	8.891***	8.984***
	(0)	(2.83e-06)	(0)	(0)	(0)	(0)
Observations	66,852	16,377	25,047	7,209	7,083	7,203
R-squared	0.325	0.715	0.032	0.260	0.255	0.260
# cities	8,378	2,544	8,376	2,505	2,464	2,503

Note: The dependent variable is the unemployment rate among those between 25 and 54 years. The main variable of interest is *Treated*, which equals 1 for cities with FFPT and 0 otherwise. Column 1 considers all the data. Column 2 restricts the dataset, taking into account only cities (communalities > 2,000 inhabitants). Column 3 is reducing the period only from 2008 to 2018. Column 4 adopts both restriction of Column 2 and 3. Column 5 is going from year 2008 to 2018 and restricts the population from 2,000 to the biggest population of FFPT cities in 2018. Column 6 is going from year 2008 to 2018, and is taking as treated only cities with FFPT before 2013. p-value in parentheses ; *** p<0.01, ** p<0.05, * p<0.1

The top row in Table 8 presents the Average Treatment Effect of FFPT on unemployment among 25–54-year-olds. The results from Table 6 are confirmed : in average, FFPT leads to more favourable changes in unemployment. While the intensity of Table 8 estimates is higher, they are also unsignificant. Except column 2, all the other columns give us p-value higher than 10%. Therefore, statistically, unemployment between 25-54 stays the same whether or not the city is applying free of charge public transit or not. According to our estimates, the hypothesis stating that the frail population might benefit more from FFPT is validated. This is in line with the theory predicting that FFPT would bring the unemployed closer to potential jobs (Hypothesis 1 of the theory part).

As Table 6, our coefficients of interest are all with a negative sign, comforting for the possibility of a decrease of unemployment thanks to FFPT. In the methodology part, we have suggested that even a few free public transport services for small villages could lead to positive results in terms of unemployment. From this perspective, it is important to observe that the 1st and 3rd columns – which are not restricting the sample in terms of cities' population size – display the lowest point estimates in table 6. Moreover, column 1 has lowest results in table 8 (though note that column 3 has the highest point estimate – albeit still statistically insignificant at 10% level). This advocates for the hypothesis that FFPT might be effective predominantly in settings where the level of services is sufficiently high (namely in sufficiently large cities).

A treatment duration of 5 years or more (6th column) seems to reinforce and make more robust our estimate, with an ATE increasing from -0.56% to -0.66% (i.e. an additional 18% decrease in unemployment once the policy is well established). This confirms the hypothesis that it would take several years before the full effects of free public transport on the local economic fabric could be felt.

Again, we decided to regress with the log of unemployment to hand the complete picture. The top row in Table 9 presents the Average Treatment Effect of FFPT on unemployment among 25–54-year-olds. For column 1, cities that have implemented FFPT see a drop of -11.0% in their unemployment rate. Like Table 8, the estimators are all negative, similar in magnitude, and can now be interpreted for all years, including those with low unemployment compared to today's rate.

Table 9 :

25 to 54 years old unemployment rate percentage changes following the FFPT implementation.

	1	2	3	4	5	6
Treated	-0.110**	-0.0824***	-0.180**	-0.0584	-0.0589	-0.0630
	(0.0350)	(0.00883)	(0.0446)	(0.148)	(0.148)	(0.130)
Observations	66,852	16,377	25,047	7,209	7,083	7,203
R-squared	0.481	0.833	0.018	0.229	0.227	0.229
# cities	8,378	2,544	8,376	2,505	2,464	2,503

Note: The dependent variable is the log(unemployment+1) rate among those between 25 and 54 years. The main variable of interest is *Treated*, which equals 1 for cities with FFPT and 0 otherwise. Column 1 considers all the data. Column 2 restricts the dataset, taking into account only cities (communalities > 2,000 inhabitants). Column 3 is reducing the period only from 2008 to 2018. Column 4 adopts both restriction of Column 2 and 3. Column 5 is going from year 2008 to 2018 and restricts the population from 2,000 to the biggest population of FFPT cities in 2018. Column 6 is going from year 2008 to 2018, and is taking as treated only cities with FFPT before 2013. p-value in parentheses ; *** p<0.01, ** p<0.05, * p<0.1

Once we exclude small towns, the magnitude of the estimated effect declines substantially - from 11% to 8% when looking the the 1968-2018 period and from 18% to 6% when looking at the 2008-2018 period. This could in part be due to the impact of few individuals on the percentage change of the unemployment rate in small towns. One person finding employment in a very small town could indeed affect the share of unemployed there quite substantially, while this would be much less the case in larger municipalities. All in all, however, our findings suggest that FFPT could be a reasonably effective way of tackling unemployment for the 25–54-year-old population living in the villages. By eliminating transportation costs, free travel restores access to work opportunities and makes the cost/benefit balance of work much more advantageous. This is in line with the hypothesis 1 of our theory part.

2) Population growth

The results for the impact of FFPT on population growth are summarized in Table 10, which again follows the format of Table 6 above. Here, we are testing the hypothesis 2 of the theory part. The idea is that FFPT policy could be attractive, and hence lead to a population growth in those cities compared to non-FFPT cities. The full sample contain 8,740 cities at 7 different time periods.[14]

[14] Note that we have one period less than previously. Even though we work with data beginning from 1968, we are manipulating growth rates. Thus year 1975 is the growth rate average between 1968 and 1975.

Table 10 :

Population growth rate changes following the FFPT implementation.

	1	2	3	4	5	6
Treated	-0.703***	-0.333	-0.439	-0.644	-0.633	-0.661
	(0.00264)	(0.334)	(0.258)	(0.253)	(0.261)	(0.259)
1982.year	0.461***	-1.375***				
	(0)	(0)				
1990.year	-0.145***	-2.108***				
	(0.00210)	(0)				
1999.year	-0.825***	-2.807***				
	(0)	(0)				
2008.year	-0.377***	-2.806***				
	(0)	(0)				
2013.year	-0.660***	-2.974***	-0.284***	-0.167**	-0.168**	-0.167**
	(0)	(0)	(5.68e-10)	(0.0382)	(0.0385)	(0.0385)
2018.year	-0.730***	-2.685***	-0.356***	0.123	0.108	0.123
	(0)	(0)	(0)	(0.127)	(0.186)	(0.127)
Constant	1.538***	3.630***	1.161***	1.043***	1.057***	1.043***
	(0)	(0)	(0)	(0)	(0)	(0)
Observations	61,174	16,244	26,214	7,837	7,686	7,828
R-squared	0.022	0.093	0.004	0.003	0.003	0.003
# cities	8,740	2,763	8,738	2,730	2,682	2,727

Note: The dependent variable is the population growth rate. The main variable of interest is *Treated*, which equals 1 for cities with FFPT and 0 otherwise. Column 1 considers all the data. Column 2 restricts the dataset, taking into account only cities (communalities > 2,000 inhabitants). Column 3 is reducing the period only from 2008 to 2018. Column 4 adopts both restriction of Column 2 and 3. Column 5 is going from year 2008 to 2018 and restricts the population from 2,000 to the biggest population of FFPT cities in 2018. Column 6 is going from year 2008 to 2018, and is taking as treated only cities with FFPT before 2013. p-value in parentheses ; *** p<0.01, ** p<0.05, * p<0.1

The interpretation of the first estimate is the Average Treatment Effect (ATE) of FFPT on population. Therefore, for the first column, the population of FFPT cities is growing -0.703% less on average than the others. Said differently, if for the control group, the average growth of population per year is 1%, the average treatment population growth would be 0.297% after the treatment. We can see that except the first column, the results are statistically insignificant. Nonetheless, all point estimates are consistently negative, which suggests that we can credibly rule out large positive effect sizes. This is important since it allows us to reject our hypothesis number 2 that "people vote with their feet".

One possible explanation for this null finding is that free transport (if not accompanied by network innovations) does not constitute a physical improvement – in contrast to the improvement of existing infrastructure or the creation of new infrastructure. Thus, it is possible that this policy innovation will ultimately have very little effect on the decision to move to that city. Household settlement criteria would remain predominantly criteria such as quality of network, size of the city, jobs availability, number of school for their children, when free transportation would remain a second-tier criterion.

Eventually, this finding may make us reflect about the unemployment changes observed previously. In fact, in view of the hypothesis of a decrease in unemployment, does this decrease come from the better mobility access for frail populations ? Or from a change in population characteristics, that would be such as young graduate workers that are already with jobs (meaning that the area is gentrifying) ? According to our findings, it can be argued that the decline in unemployment is probably due to better access to public transport (said differently, this measure is profiting to citizens already living in the area) rather than to a change induce by a growing attractiveness following the end of transport fees for the users (leading to incoming new citizens). Indeed, cities with free public transport have tended to have lower population growth than other cities, suggesting that this is not necessarily an attractiveness shock, but rather an effective social support for existing residents. In order to confirm this hypothesis, future research could focus on the evolution of the socio-professional categories of households in these areas, and/or on real estate prices.

3) Car ownership

Table 11 is slightly different from the previous ones. The statistical sample is going from 2006 to 2018. Thus, we remove the columns 1 and 2 of the previous tables that were going from 1965 to 2018. This leaves us with column 1, the full sample, column 2, which is excluding villages (cities with less than 2,000 inhabitants), column 3, which has as lower bound cities with more than 2,000 inhabitants and has as higher bound the biggest FFPT-implementing city, and eventually column 4, which as only the 2,000 inhabitants lower bound, and that restrict treated cities to those that have implemented FFPT before 2013.[15] In all cases, we report the point estimate with associated p-value in parentheses.

As before, the first row of the table gives us the Average Treatment Effect. For the first column, we interpret the coefficient as follows: as a result of free public transport, the number of cars tends to increase by 0.00186 units per household (the result is not significant). The ATE found in the first column might come from the fact that our analysis is also including villages. They still might suffer from long distance to certain point of interest (supermarket,

[15] The reason why we choose those settings are explained in the 15-64 unemployment part.

Table 11 :

Car ownership changes following the FFPT implementation.

	1	2	3	4
Treated	0.00186	-0.0109***	-0.0113***	-0.00964**
	(0.774)	(0.00306)	(0.00216)	(0.0118)
2007.year	0.00845***	0.00380***	0.00393***	0.00380***
	(0)	(7.20e-05)	(5.29e-05)	(7.27e-05)
2008.year	0.0157***	0.00566***	0.00588***	0.00566***
	(0)	(3.22e-09)	(1.45e-09)	(3.37e-09)
2009.year	0.0219***	0.00784***	0.00815***	0.00785***
	(0)	(0)	(0)	(0)
2010.year	0.0269***	0.00899***	0.00937***	0.00897***
	(0)	(0)	(0)	(0)
2011.year	0.0324***	0.00995***	0.0104***	0.00993***
	(0)	(0)	(0)	(0)
2012.year	0.0387***	0.0124***	0.0130***	0.0124***
	(0)	(0)	(0)	(0)
2013.year	0.0429***	0.0146***	0.0153***	0.0146***
	(0)	(0)	(0)	(0)
2014.year	0.0477***	0.0179***	0.0186***	0.0179***
	(0)	(0)	(0)	(0)
2015.year	0.0511***	0.0201***	0.0207***	0.0201***
	(0)	(0)	(0)	(0)
2016.year	0.0557***	0.0230***	0.0237***	0.0230***
	(0)	(0)	(0)	(0)
2017.year	0.0593***	0.0236***	0.0243***	0.0236***
	(0)	(0)	(0)	(0)
2018.year	0.0632***	0.0261***	0.0269***	0.0261***
	(0)	(0)	(0)	(0)
Constant	1.472***	1.351***	1.360***	1.351***
	(0)	(0)	(0)	(0)
Observations	114,226	32,526	31,837	32,487
R-squared	0.054	0.056	0.059	0.056
Number of communalities	8,787	2,502	2,449	2,499

Note: The dependent variable is the mean of the number of cars per household. The main variable of interest is *Treated*, which equals 1 for cities with FFPT and 0 otherwise. Column 1 considers all the data. Column 2 restricts the dataset, taking into account only cities (communalities > 2,000 inhabitants). Column 3 restricts the population from 2,000 to the biggest population of FFPT cities in 2018 (65.817 citizens). Column 4 is taking cities treated before 2013. p-value in parentheses ; *** p<0.01, ** p<0.05, * p<0.1

school, health centre, work …) which doesn't enable to totally give up motorized vehicles as easily as easily as cities.

When we select only cities with more than 2,000 inhabitants (columns 2, 3 and 4), we see that households in FFPT areas own on average -0.01 car less compared to the other cities in our sample that have an average of 1.377 cars per household in 2018. This represents a decrease of 0.8% in the number of cars per household. Thus, this confirms the potential substitution effect of the car for public transport. This linked the story exposed in Dunkirk where 5% of a study respondents claims to not have buy a new car or abandon one of his car.[16]

After at least 5 years of treatment (column 4), there is no evidence of a strengthening of the treatment effect (the estimate remains stable around -0.01 unit). It is possible that the free transport policy acts on the decision of households to not buy (or give up) a new vehicle at time T, when the policy is implemented, but less so afterwards.

We should keep in mind that free transport might be one of the policies of a broader urban mobility and/or sustainable development plan. This policy may be accompanied by other policies that may also reduce the attractiveness of the car, such as making car spaces more scarce or more expensive, increasing the supply of public transport, or providing bicycle lanes. Thus, car use reduction might be the effect of a broader package of policies rather than the only effect of FFPT.

[16] cf. literature.

VII) Conclusion

In this thesis, we have collected data on French municipalities and set up a difference-in-differences regression approach to assess whether – and, if so, how, Fare-Free Public Transportation impacts upon local unemployment, population growth and car ownership. To the best of our knowledge, this is one of the first empirical studies of such effects, and hopefully can lay the foundation for further empirical research into the impact of free public transport. What we can retain from the main regressions estimates is threefold.

First, we find a reduction in unemployment of 0.517% on average for the 15-64 unemployment rate when the city has implemented FFPT for more than 5 years, which is statistically significant beyond the 10% level. Across our estimates, very similar effect sizes are observed as long as the sample is restricted to municipalities with at least 2,000 inhabitants, which suggests a substantively meaningful reduction in employment in FFPT areas with high enough service provision. Although in absolute terms unemployment does not fall significantly for the 25-54 age group, there is extremely strong and robust rates of change once the log transformation is done (up to -18% unemployment for municipalities once free transport is implemented!). Despite the fact that it is likely due to statistical vulnerability of small towns to unemployment changes, it shows that FFPT has some effects even on slightly treated areas.

Second, we find no statistically significant effect of FFPT on population growth in the city. While statistically insignificant, the weakly negative point estimates in fact suggest that we can safely rule out large positive effects of FFPT on population growth. This goes against theoretical arguments based on Tiebout sorting. Yet, this non-result may simply reflect the fact that making public transport free is not a sufficiently important change – in terms of its budgetary impact on individuals – to compensate for any costs of migration. Given that costs of migration across municipal borders tends to be substantial, it only becomes worthwhile if the difference in utilities from distinct places is large enough. Based on our results, we would infer that making public transport free does not meet this threshold for any substantial number of people.

Finally, our findings indicate a slight, but statistically significant, impact of FFPT on household's car ownership. Specifically, our point estimates indicate that car ownership on average decreases by 0.8%. Although this is arguably a very small effect, it should be remembered that it is likely to be exclusively driven by changes in households forsaking on a second (or third?) car.

Several avenues of future research are suggested by our analysis. First, although the very first experiments with free transport date from the 1960s in the USA, 1970s in France, Free public transport has only been democratized since the end of the 2000s in France. The available data and the recent nature of this policy do not allow for catching the full effect of those policy. We would be curious to retry the experience 10 years later with the same settings.

Second, as mentioned above, it is the companies that pay for the loss of revenue from the users' tickets. We can ask ourselves if this does not have an impact on the location of companies, which would see their costs increase and would prefer to locate elsewhere. At the same time, free public transportation could attract workers, and make the companies inside the concerned area more desirable. Then, companies could set up there and hope to hire more easily. Observing the behavior, not only of households, but also of businesses with respect to this free transport policy can greatly contribute to orienting the attractiveness policies of the cities concerned.

Third, to return to the Tiebout sorting, it will also be necessary to look at the changing composition of cities imposing free rides. Can we notice a real change in socio-economic classes, in the type of family (we can imagine that families with children or teenagers prefer free transport to allow them to move easily for example), or in the convictions of families (search for a greener, healthier city...)?

Finally, our analysis only looks at unemployment rate, but does not measure economic activity in the area. Future research thus would do well to extend our analysis by incorporating direct measures of the level of (economic) activity.

VIII) References

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