Do price reductions attract customers in urban public transport? A synthetic control approach

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SHORT SUMMARY

In this paper, we assess the demand effects of lower public transport fares in Geneva, an urban area in Switzerland. Considering a unique sample based on transport companies' annual reports, we find that, when reducing the costs of annual season tickets, day tickets, and hourly tickets (by up to 29%, 6%, and 20%, respectively), demand increases over five years by about 10.6%. To the best of our knowledge, we are the first to show how the synthetic control method can be used to assess such (for policy-makers) important price reduction effects in urban public transport. Furthermore, we propose an aggregate metric that inherits changes in public transport supply (e.g., frequency increases) to assess these demand effects, namely passenger trips per vehicle kilometre. This metric helps us to isolate the impact of price reductions by ensuring that companies' supply changes do not affect estimators of interest.

Keywords: policy evaluation, price reduction, urban public transport pricing, synthetic control method

1. INTRODUCTION

The transport sector is a pivotal contributor to air pollution. Globally, approximately 27% of CO_2 emissions and energy consumption are caused by the transport sector; in the European Union, the figure amounts to about a third (Batty et al., 2015). Therefore, the transport sector also causes negative externalities, which means a situation in which the action of a person imposes a cost on another person who is not a party to the transaction. Private car use will lead to even greater levels of such negative externalities, which a shift in transport mode towards public transport could help to reduce. Lower fares are a frequently discussed tool to motivate individuals to use public transport (see, e.g., Redman et al., 2013).

However, policy-makers must know how existing and potential customers respond to such lower fares. In reality, it is generally challenging to identify the causal effect of lower fares on public transport demand as transport supply changes over time. Therefore, we propose an aggregate metric that inherits a transport company's supply in public transport demand. The metric is composed of passenger trips per vehicle kilometre. Moreover, considering CO_2 emissions, an increase in the metric points to an average emission decrease by each passenger.

In our comparative case study,[1] we use this metric as the outcome variable to analyze lower fares empirically in the case of Geneva, an urban area in Switzerland. There, the electorate decided to

[1] Note that this paper is based on a more extended paper, see Wallimann et al. (2023).

reduce the price of state-owned public transport, which Geneva introduced in December 2014. The reduction amounted to up to 29% for annual season tickets, 6% for day tickets, and 20% for tickets valid for one hour. The policy intervention was the largest price reduction in a long time. As a result, the annual season ticket in Geneva now costs 500 Swiss francs for adults (previously 700 Swiss francs) and 400 Swiss francs for seniors and juniors (previously 500 and 450 Swiss francs, respectively). These prices are more than 200 Swiss francs less than those charged by other Swiss cities. For instance, annual season tickets in Lausanne, Berne, Basel, and Zurich cost 740, 790, 800, and 782 Swiss francs, respectively. The same is the case for single-fare tickets amounting to 3 Swiss francs in Geneva.

To illustrate the price-reduction effect, we analyze the case of TPG, the main operator in the city of Geneva, and its agglomeration belt. To this end, we apply the synthetic control method (Abadie, Diamond, and Hainmueller, 2010, Abadie and Gardeazabal, 2003) to construct a synthetic TPG, a counterfactual that mimics the demand the company would have experienced in the absence of the price reduction. The thing to notice is that the methodology uses a data-driven procedure to create the synthetic TPG from comparable Swiss transport operators.

2. METHODOLOGY

In this section, we outline the synthetic control method used in our empirical analysis. Second, we present the assumptions underlying our analysis.

Methodology and implementation

Let D denote the binary treatment 'price reduction' and Y the outcome 'public transport demand'. The treatment D, the result of the initiative in Geneva, affects one unit (TPG). All the other units (transport companies) in our data are not exposed to the price reduction and thus constitute the control group. We can define the observed outcome of TPG, our unit of interest, as

$$Y_t = Y_t^N + \alpha_t D_t.$$

Y_t denotes the observed outcome, Y_t^N the outcome without the treatment, and α_t the treatment effect at time t. It is important to note that the treatment D takes the value 0 for all units during the period $t < T_0$, with T_0 indicating the introduction of the treatment. This is because also TPG was not exposed to the price reduction during the pre-treatment period. Only looking at the post-treatment period permits to define the treatment effect as

$$\alpha_t = Y_t - Y_t^N.$$

As we observe Y_t, we merely need to estimate Y_t^N, the public transport demand of TPG without the policy intervention. Using statistical parlance, Y_t^N is a counterfactual. That is the outcome one would expect if the intervention had not been implemented. To determine Y_t^N, we use the synthetic control method of Abadie and Gardeazabal (2003) and Abadie, Diamond, and Hainmueller (2010). To construct the synthetic control unit (Y_t^N), the synthetic control method uses a data-driven procedure. In our study, the counterfactual Y_t^N, the synthetic TPG, is created out of already-existing companies of the control group, the so-called 'donor pool'. For this purpose, the methodology assigns a weight to each transport company in the control group. These weights are non-negative and sum up to one. On the one hand, we assign large weights to companies with a sizeable predictive power for TPG. On the other hand, transport companies in the control group with a low predictive power receive a small or a zero weight. The goal is to minimize the difference between TPG and the synthetic TPG in the period $t < T_0$, the pre-treatment period. To discuss the success of this endeavor, we calculate the mean squared prediction error (MSPE) of the outcome variable between TPG and the synthetic TPG. In implementing the synthetic control method, we use the synth and SCtools packages for the statistical software R by Hainmueller and Diamond (2015) and Silva (2020), respectively.

To empirically challenge the results, we calculate the corresponding 95% bootstrap confidence intervals to the average treatment effect. Therefore, we randomly draw control units with replacement from our donor pool 2,000 times to arrive at these confidence intervals. In every sample, we construct a synthetic TPG and estimate the average gap between TPG and its counterfactual.

Assumptions

Identification requires statistical procedures, as explained in the previous subsection. However, on the other hand, ensuring that our calculation identifies the effect of the price reduction also relies on assumptions about how the world, here the world of public transportation, works (see, e.g., Huntington-Klein, 2021). Therefore, in the following, we discuss the contextual assumptions underlying our analysis (see also Abadie, 2021).

Assumption 1 (no anticipation) is satisfied when the public transport demand in Geneva did not change due to forward-looking customers reacting in advance to the policy intervention. To this end, the price reduction effect would be biased if TPG's travelers had already used public transport before the intervention because they knew that prices would fall later.

By *Assumption 2 (availability of a comparison group)*, there exists a donor pool. The assumption is satisfied when we have a control group with characteristics that are, by assumption, comparable to the treated unit. That implies that other public transport companies do not sharply lower fares in our natural experiment.

Assumption 3 (convex hull condition) is satisfied when pre-treatment outcomes of the synthetic counterfactual can approximate the outcomes of the treated unit. Using statistical parlance, the pre-treatment outcomes of the treated unit are not 'too extreme' (too high or low) compared to the outcomes of the donor pool.

Assumption 4 (no spillover effects) is fulfilled when the price reduction has no spillover effects, eighter positive or negative, on other transport companies in the donor pool. An obvious failure of this assumption would be a decrease in public transport demand in other Swiss cities because their residents perceive the ticket costs as too high after the price reduction in Geneva.

Assumption 5 (no external shocks): Applying the synthetic control method, we assume that no shocks occur to the outcome of interest during the study period (see, e.g., Abadie, 2021). In our case, this condition is challenging since public transport companies expand the network from time to time, which typically affects the demand for public transport (see, e.g., Brechan, 2017, Holmgren, 2007). To account for such changes in supply, we propose an aggregate metric that breaks down the demand for public transport per company's supply, which we use as our outcome variable. More precisely, we calculate the ratio of passenger trips per vehicle kilometre, being robust against changes on the supply side. Finally, note that, to our knowledge, no large-scale road or parking policy was introduced in the areas of interest during the study period.

3. RESULTS AND DISCUSSION

We subsequently introduce the data underlying this paper. Then, we present the results of applying the synthetic control method, evaluate their significance and investigate their robustness.

Data

To investigate the effect of the policy intervention in Geneva, we use the annual reports of Swiss transport companies, which the Swiss National Library systematically archives. We systematically gathered the most relevant performance indicators from public transport companies for our dataset. TPG operates mainly in the city of Geneva, the densest and second largest city in Switzerland, and its agglomeration belt. Using the synthetic control method, we must choose each unit in the donor pool judiciously to provide a reasonable control for TPG, the treated unit (see Assumption 2). Therefore, we only consider transport companies that operate trams and buses primarily in cities with more than 50,000 inhabitants. These are Bernmobil (Berne), BVB (Basel), SBW (Winterthur), TL (Lausanne), TPL (Lugano), VB (Biel), VBL (Lucerne), VBSG (St Gallen), and VBZ (Zurich).

First, we collected the number of passenger trips, which are standardized in Switzerland. The number of passenger trips counts how many passengers enter a company's vehicle per year. Passenger trips are essential, as we want to measure the increase in public transportation use. Today, companies mainly count passengers automatically, but this was often done by hand in the past. This change in the counting system happened in Geneva from the years 2015 to 2016. Therefore, we adjust our TPG data from 2016 to 2019 based on the observed growth rate of the passenger trips to have a refined panel dataset. Since 2005, TPG has experienced the highest increase in passenger trips. However, TPG has also experienced a high increase in vehicle kilometres. The increase results from the extension of tram routes. Therefore, to mitigate changes in supply, i.e., external shocks increasing companies' networks (see Assumption 5), we use the previously discussed aggregate metric of passenger trips per vehicle kilometre as the outcome variable.

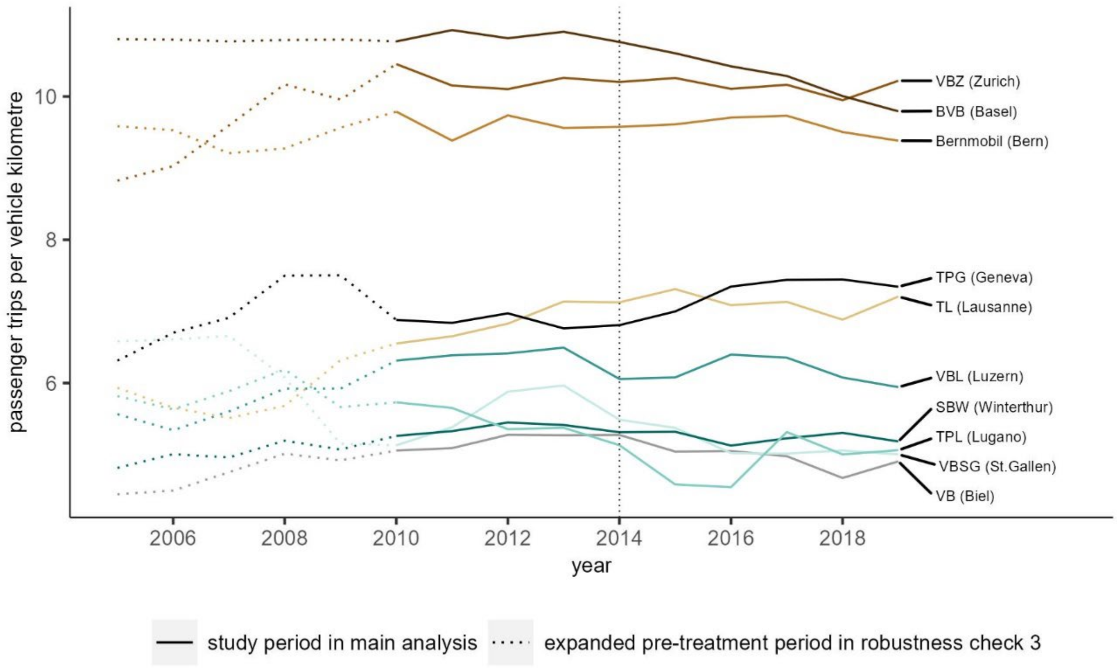

Figure 1 Passenger trips per vehicle kilometre. Note that we restrict our pre-treatment period to 2010 to 2014 (solid lines).

Controlling for supply changes also makes sense, as several studies show considerable effects of vehicle kilometers on demand. For instance, Holmgren (2007) estimates a short-run supply (vehicle kilometres) elasticity of 1.05. Based on this meta-analysis, we assume a considerable supply elasticity of about 1 when applying the ratio. However, and also a thing to notice, due to a substantial increase in vehicle kilometers plied by bus lines in Geneva's agglomeration belt from 2008 to 2010, the ratio in Geneva declined. This is because the aggregate change in TPG's supply occurred in the subarea where public transport is relatively poorly utilized. Therefore, we restrict our pre-treatment period to the years 2010 to 2014. However, collecting several observations on the unit of interest (TPG) and the donor pool is crucial before the price reduction (Abadie, 2021). Therefore, we also perform a robustness check with a more extended pre-treatment period. Moreover, we also oppose our results to estimations without the metric and thus use only passenger trips as the outcome variable. This robustness check is crucial, as unexpected low (or high) supply elasticities could be an alternate explanation of the treatment effect.

The effect of the price reduction

To construct the synthetic TPG, the synthetic control method assigns weights among the control group companies. VB (Biel) receives the highest weight with 0.400, while BVB (Basel) has the second-highest weight with 0.162, and the VBSG (St Gallen) has a zero weight. Figure 2 plots the outcome variable, equal to passenger trips per vehicle kilometre, of TPG and the synthetic TPG from 2010 to 2019. We can easily observe that the two trajectories track each other close in the pre-treatment period, i.e., the pre-price reduction period. Thus, the mean squared prediction error (MSPE) of the outcome variable between TPG and the synthetic TPG amounts to a small figure of 0.009. Therefore, our synthetic TPG is a sensible counterfactual of the outcome we would expect if the intervention had not been implemented. While demand from customers of the synthetic TPG continued its slightly downward trend, the demand for TPG increased. This difference is relatively constant over four years, from 2016 to 2019.

Compared to the synthetic counterfactual, the demand increased by, on average, about 0.72, an increase of 10.6% compared to 2014. Thus, we can infer a positive effect on demand in Geneva due to the price reductions. Randomly drawing nine control units with a replacement from our donor pool leads us to bootstrap confidence intervals. The average estimated effect's corresponding 95% bootstrap confidence interval is [0.423; 0.870].

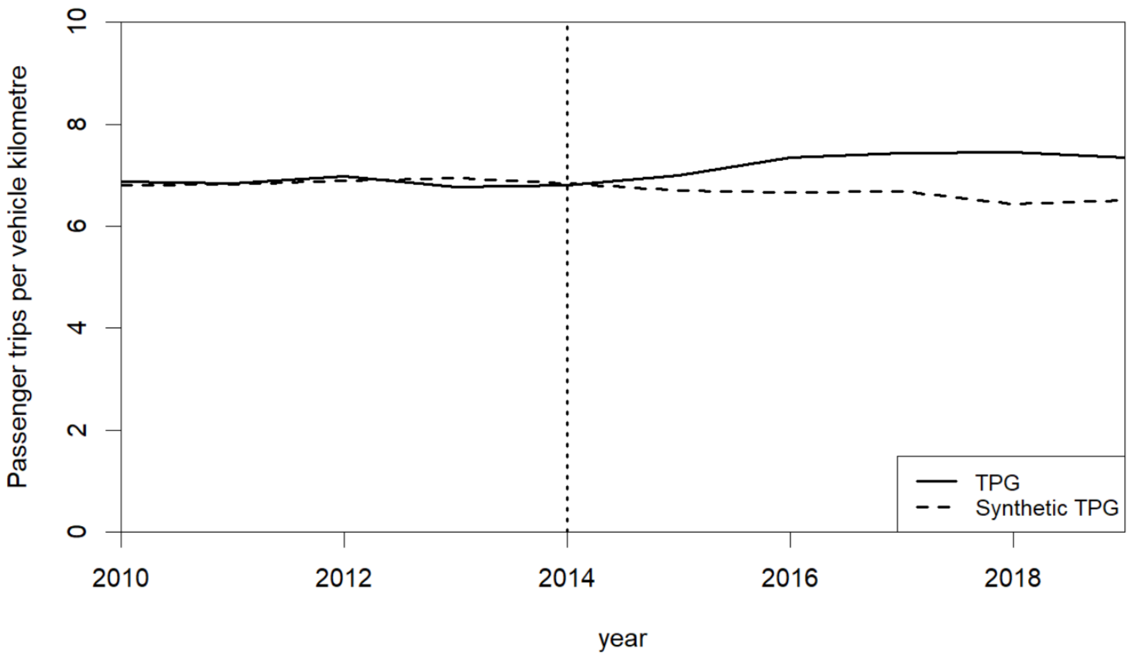

Figure 2: Demand development of TPG and the synthetic TPG

Robustness analysis

Here, we challenge our assumptions and study design by performing robustness investigations. First, as a methodological robustness check, we apply a recent development of the synthetic control method, the synthetic difference in differences approach of Arkhangelsky et al. (2019), to demonstrate the goodness of our results. Second, we expand our pre-treatment period. Third, we expand our donor pool with companies operating in cities with fewer than 50,000 inhabitants. Fourth, we estimate the effect of the lower fares on the number of passengers (and not the number of passengers per vehicle kilometre). Moreover, in the fourth robustness check, the synthetic TPG does not mimic TPG in the pre-treatment period appropriately. Therefore, in a final robustness investigation, we re-estimate the effect on the number of passengers using the synthetic difference in differences approach.

Table 1: Estimates summary of robustness checks

Check	Modification	Price effect
1	Method (SDID)	10.0%
3	More units in the donor pool	10.5%
2	Expanded pre-treatment period	9.0%
4	Passenger trips as outcome variable	Insufficient fit
5	Passenger trips as outcome variable and method (SDID)	3.7%

Note: In robustness checks 1, 2, and 3, we use passenger trips per vehicle kilometres as the outcome variable

In the first, second, and third robustness checks, we use passenger trips per vehicle kilometres as the outcome variable (see Table 1). These robustness checks show that the estimate is robust when we modify the study design, i.e., applying the synthetic difference in differences approach, longer pre-treatment period, or more companies in the donor pool. In the fourth and fifth robustness investigations, we replace our metric with the original number of passenger trips. We consider the synthetic difference in differences methodology more appropriate to analyze the outcome variable passenger trips. However, note that Assumption 5 (no external shocks) is violated when using the outcome variable passenger trips regardless of the methodology.

The results in the fifth robustness check are lower, which shows that our estimate crucially depends on whether we consider the influence of the vehicle kilometres. The demand effect amounts to 3.7% when we apply the synthetic difference in differences methodology. A demand increase of 3.7% is even lower than naively comparing the passenger trips of TPG after and prior to the price discount, amounting to 5.7% additional trips. Moreover, when calculating bootstrap estimates of the effect, we do not get any negative values. The 95% bootstrap confidence interval of the average estimated effect points to an increase of between 2.0% and 12.4%, inclusive. Therefore, we conclude that the effect of 3.7% additional demand is a potential lower bound of the effect.

Elasticities

Considering the revenue shares per ticket category of 2014, we assess an overall price discount of 12.6%. Based on the price discount of 12.6%, we get corresponding point elasticities of demand of -0.84 and -0.29 of our main result and the lower bound, respectively. Therefore, we show that price reductions in urban areas with high-quality public transport attract customers. However, the demand effect is too small to compensate for the loss of revenue due to lower prices. Using the metric passenger trips per vehicle kilometre, we assume high supply elasticities, i.e., about 1, due to findings in the literature (Holmgren, 2007). On the other hand, as a word of caution, high supply elasticity might be lower when public transport quality is high, e.g., Axhausen and Fröhlich (2012). In such a case, increasing or decreasing vehicle kilometres could influence the metric and, therefore, the estimate of interest.

4. CONCLUSIONS

We assess the demand effect of lower urban public transport fares and find that the price reduction in Geneva leads to a demand increase of about 10.6%. To isolate the effect of our mechanism of interest, the price reduction, we propose an aggregate metric inheriting supply changes of public transport networks. This makes sense as we can block off the effect of increasing and decreasing frequencies as an alternate explanation of demand effects, being in the context of public transport of crucial importance. Moreover, robustness investigations show that the estimate is robust when we modify the study design, i.e., applying the synthetic difference in differences approach, longer pre-treatment period, or more companies in the donor pool. However, the estimate is significantly lower (i.e., 3.7%) when we consider the outcome variable passenger trips and do not isolate the price reduction effect from the supply effects, i.e., representing the lower bound of the effect.

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