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Impact evaluation of a cycling promotion campaign using daily bicycle counters data: the case of Cycling May in Poland

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Abstract

The promotion of active and sustainable transport modes as an alternative to motorised individual transport has become a key policy priority in Europe, to reduce air pollution, road congestion, noise, traffic injuries, and the adverse health outcomes of sedentary lifestyles. Policymakers are implementing a wide range of measures to encourage this shift in attitudes and behaviours. These interventions are most valuable when targeting children and young people, as they weigh in habit formation and result in longer term benefits. More specifically, soft transport policies include measures like informational and educational campaigns, marketing techniques, personalized services and incentives. Among this type of policies, the gamification approach based on a competition mechanism and relative reward is applied to promote cycling behaviour, especially directed towards children.

In this study we evaluate the Cycling May policy, a wide campaign aimed at promoting commuting to school by bicycle and implemented in several cities in Poland, and targeting schoolchildren and their families. We apply a quasi-experimental design based on observed daily bicycle counts on bicycle lanes in the targeted city of Gdansk and in a control city, over a three-years period. Estimates from a difference-in-difference panel regression show that the policy generated a 18% average increase in daily bicycle traffic. Despite the positive estimated effect during the intervention, our findings suggest that the behavioural change is not sustained after the intervention ends, consistently with findings from similar research.

Keywords: soft transport policy, active transportation, cycling intervention, quasi-experimental method, difference-in-differences, policy impact evaluation

Highlights

- We evaluate the effect of the Cycling May campaign using three years of daily bicycle traffic data.

- We apply difference-in-differences panel regression to estimate the causal impact of the intervention.
- The policy increased average bicycle traffic by 18% during the intervention months.
- The policy effect was sizeable during the intervention, but the long-term effects are less clear.

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1. Introduction

An emerging challenge faced by many cities worldwide is the growing use of motorised individual transport with associated problems of air pollution, road congestion, noise, and traffic injuries. In particular, road transport accounts for the highest proportion of overall transport greenhouse gas emissions (GHG; in 2019 road transport emitted 72% of total transport GHG). Over the last five years, the number of cars relative to total population has grown in almost all EU Member States (Eurostat, 2017), and this increased car usage represents a threat to the environment, the economy and citizens' health (Möser & Bamberg, 2008). Hence, policymakers around the world are encouraging a public shift towards sustainable and/or active transport modes. Widespread switch towards sustainable transport modes could however be hindered by technological and budget constraints. Nevertheless, active transport models such as cycling represent viable alternatives to car usage, at least over short- to medium-length distances like every day commuting to work or school.

Cycling is a relatively fast, flexible, and environmental-friendly activity; it allows for cheap and direct trips and does not contribute to traffic congestion and air pollution. It is also an easy and convenient way to reduce sedentary behaviour, enhancing both health and well-being (Larouche et al., 2014; Rodrigues et al., 2020). Nowadays, many European cities implement policies aimed to promote cycling. Making cities bicycle-friendly by providing an adequate cycling infrastructure is a prerequisite for obtaining an increase in usage of bicycle (Dill & Carr, 2003; Kraus & Koch, 2021). On top of that, "soft" transport policies aimed at shifting individuals' attitudes and behaviour towards the use of bicycle could be implemented. Soft policies use measures like information campaigns, marketing techniques, personalized services and incentives in order to motivate individuals to change their behaviour (Cairns et al., 2008; Möser & Bamberg, 2008; Ogilvie et al., 2004). Examples of implemented soft measures to promote bicycle usage include promotion and training events (Rose & Marfurt, 2007), travel awareness programs (Mutrie et al., 2002), individualised marketing (Brög et al., 2009), targeted bicycle promotion campaigns (Höchli et al., 2019; Uttley & Lovelace, 2016), competitions/ gamification (Weber et al., 2018); and can be directed towards overall population (Rissel et al., 2010) or target specific sub-groups, e.g. employees (Höchli et al., 2019; Mutrie et al., 2002), university students (Uttley & Lovelace, 2016) and school pupils (Crawford & Garrard, 2013). In particular, children could play a prominent role in transport mode switch. Educating children to the use of active transport modes might shape positive attitudes and improve current and future behaviour, as well as induce a shift on parents' behaviour (Fyhri et al., 2011; Mackett, 2013). A further reason to implement soft transport policy measures targeting children refers to the increasing level of their sedentary lifestyle: according to the latest data, three out of four children aged 6-17 do not meet the minimum physical activity time as recommended by WHO (Data Resource Center for Child and Adolescent Health, 2016).

Hence, promoting regular cycling to school might enhance a more active lifestyle for children and adolescents, providing health benefits for hearts, bodies and minds (World Health Organization, 2020). In the long-term, it may contribute to physically active lifestyle in the adulthood and better future transportation habits (Telama et al., 2014; Dollman & Lewis, 2007). For these reasons, several existing soft transport policies aimed at increasing the use of active transportation modes are directed at school aged children.

The objective of the present study is to quantitatively evaluate the impact of a cycling promotion campaign targeted towards children. We consider the Cycling May campaign implemented in Poland, a large intervention aimed at increasing bicycle usage for commuting to school, which follows a gamification approach. To evaluate the impact of the intervention we follow a quasi-experimental approach based on a difference-in-difference regression model and observational data. The model is estimated on daily records from bicycle counters in two main Polish cities, considering several waves of the intervention over a three years period. The novelty of this study rests mainly on the quantitative estimation of the causal effect of the intervention on bicycle traffic. To the best of our knowledge, most of the existing evaluation studies of cycling transport policies rely on self-reported data, and – while allowing to gain insights on attitudes and behaviour – might be affected by several bias (e.g. self-selection, social desirability bias, memory bias, etc.). Our quasi-experimental, difference-in-difference approach allows to obtain causal estimate of the effect of the intervention, providing crucial information for policy makers and planners about actual change in bicycle traffic triggered by the considered intervention.

The paper is structured as follows: Section 2 reviews the literature on policy evaluations of soft policies to promote active transport modes, with a specific focus on interventions aimed towards children; Section 3 describes the Cycling May intervention; Section 4 presents the evaluation methodology and the data; Section 5 describes the results; and Section 6 draws some implications from our findings and provides concluding remarks.

2. Literature Review

Impact evaluation research on transport policy interventions proliferated over the last decades. Several studies evaluate the effect of interventions aimed at reducing car use and promoting shifts towards active transportation modes through soft policy measures. Given the aim of the paper, we summarize here the existing evidence from studies that specifically evaluate soft transport policy interventions aimed at changing transport behaviour in everyday commuting to work or school. We especially focus on cycling-related studies targeting children and discuss the methodological issues related to the identification and quantification of policy impact evaluation.

As a general result, Semenescu et al.'s (2020) review and meta-analysis on effectiveness of soft interventions in reducing car use over the last 30 years suggests a significant reduction of 7% in the car modal share. The review also indicates that the type of intervention and the psychological variables targeted by the intervention act as moderators of the intervention effectiveness. Therefore, while soft transport policies might successfully reduce car use and increase the use of active transportation modes, factors related to specific characteristics of the interventions could hinder their effectiveness.

Considering soft policies aimed at increasing cycling in everyday commuting, evaluations cover different types of measures, including cycling competitions, informational and educational campaigns, cycling events, or a mix of infrastructure improvements with promotional strategies. The evidence on the estimated policy effect is mixed, and greatly depends on the method used for impact evaluation and on the choice of the outcome measure.

Competition is an effective way to engage employees and students in changing their transport behaviour: Höchli et al. (2019) evaluated the effect of a cycling competition among employees of various Swiss companies using self-reported data and questionnaires administered during the intervention. They report a significant increase in cycling frequency among participants during the intervention, a diminishing effect over the following 2 months, and a return to the baseline levels three months after the event. Uttley and Lovelace (2016) considered an inter-departmental competition designed to encourage staff and students at the University of Sheffield to cycle, and observed that the increased cycling frequency is sustained in the two years follow up by 26% of participants. However, this study has a small sample size, no control group, and is based on self-reported data from a selected sample, which challenges the credibility of the findings. More generally, there is broad evidence that interventions based on competition show a positive effect during the intervention, but also much smaller or no effects in the longer term. This is a particularly important limitation, given that the economic, environmental and health-related cycling benefits accrue over the long-term.

Other studies investigated the effect of informational and educational campaigns through randomized control trials relying on self-reported data, such as Audrey et al.'s (2019) evaluation of an informational campaign aimed towards increasing walking as a commuting mode; Diniz et al. (2015) assessment of an educational intervention on commuting by bicycle; and Mutrie et al.’s (2002) paper on self-help intervention to increase active commuting behavior. The first study found no effect on the observed level of physical activity of employees after the intervention; the second study found a significant but small increase in cycling; while in the third study a significant increase in walking and no effect on cycling are reported.

The effectiveness of interventions to increase active commuting to school has also been the subject of research. For instance, Crawford & Garrard (2013) and Wen et al. (2008) analysed cycling and walking to school interventions implemented in Australia. The first study applies a mixed method approach (including a control group, observed and self-reported quantitative and qualitative data) to evaluate an intervention including educational activities and infrastructure improvements; they found little evidence of an overall increase in active transport to school across participating schools. Wen et al.’s (2008) study focused on an informational campaign to increase walking to school; they randomly assigned the intervention to schools and collected pre-post self-reported data form students and parents, finding an inconsistent effect: while parents reported a significant increase in active transportation among their children, no difference was observed in students reported transport behaviour.

Popular initiatives aimed at increasing active commuting among school-aged children are “walking bus” and “bike train” programs, which involves a group of children walking or cycling to school together assisted by an adult leader. However, their effect on transport behaviour is rarely evaluated and the results are mixed. For example, Keall et al. (2018) conducted a survey among parents of children involved in “walking buses” and, based on a qualitative assessment, concluded that the program is beneficial in creating walking habits among children and their families. Mendoza et al. (2011) conducted a pilot cluster randomized controlled trial in order to evaluate the effectiveness of walking bus programs in 8 elementary schools in Houston. The evaluation results suggest a significantly increased frequency of active commuting and daily moderate-to-vigorous physical activity among involved children during the intervention. A similar randomized controlled trial was conducted by the same author in order to evaluate ‘bike train’ programs in four elementary schools in Seattle (Mendoza et al., 2017). Both the percentage of cycling trips obtained from surveys and the moderate-to-vigorous physical activity measured by accelerometers and GPS were found to be significantly higher in the intervention versus control group. On the other hand, the evaluation conducted by Sayers et al. (2012) based on data from accelerometers showed no differences in daily minutes of moderate-to-vigorous physical activity between children participating in walking bus and children not involved in the intervention.

None of the studies above evaluated the long-term results of these types of programs on daily transport behaviour.

Interesting results emerge from evaluations of mixture policies including infrastructure improvements. The study by McDonald et al. (2013), which evaluate the Safe Routes To School campaign in Oregon, is one of the few evaluations considering a quasi-experimental setting. The study relies on data from three types of surveys collected over five waves and fourteen schools. Results show that the implementation of soft measures alone (education and encouragement) generates a 5% increase in cycling, while a mix of soft and hard measures (including infrastructure improvements) leads to a 11% and 19% increase in cycling and walking, respectively. The Nevada Moves Day is a one-day state-wide celebration within the Safe Routes To School program, whose effect has been evaluated by Bungum et al. (2014) based on data on the number of walkers and bikers from one targeted school and one control school, before, during and after the event. On the day of the event active transportation rates were 10.9% higher compared to the control school, but one week later they returned to baseline levels.

The intervention which is most similar to the Cycling May campaign in Poland is probably the Beat the Street campaign in the United Kingdom[1]. This policy adopts a gamification approach based on competition and rewards, although it includes several measures and extends beyond school commuting. As part of Beat the Street, Hunter et al. (2015) evaluated an international walk-to-school competition spanning over a 4-week period, involving schools based in major cities in England and Canada, using uncontrolled pre- and post-mixed methods (i.e. swipecards, survey, interviews and focus groups). The primary outcome was the number of walks to/from school objectively measured using swipecard technology system on a daily basis. The study findings highlight an increased interest and engagement in walking to school, but a gradual decline in the average number of children walking to and from school during the competition period. Similarly to what can be observed for competition measures for employees, interventions based on gamification seems to have a small effect in the longer term. Coombes and Jones (2016), evaluated a 9-weeks active travel to school competition – also part of the Beat the Street program – in Norwich, UK, with one targeted and one control school based on recorded physical activity levels and travel diaries, finding non-significant results.

In relation to the type of data used in soft transport policy evaluations, most studies are based on self-reported data (see e.g. Aldred et al., 2019; Braun et al., 2016; Jia & Fu, 2019; Mingzhu et al., 2019; Nielsen

[1] See https://www.gov.uk/government/case-studies/beat-the-street-getting-communities-moving for more information.

& Haustein, 2019). Some exceptions worth mentioning are represented by the study from Hong et al. (2020), that exploits data from an activity-tracking app and estimates the impact of the provision of safe cycling infrastructure on bicycle traffic with a fixed-effects panel regression model controlling for weather conditions; Kuo et al. (2021) use number of trips from bikeshare stations to estimate the impact of public events on bikeshare utilization; Wang and Lindsey (2019) estimate the effect of increased accessibility to bike share stations on bike share use, considering individual trips; de Kruijf et al. (2021) investigate the impact of weather conditions on e-bike usage based on individual GPS data.

Focusing on cycling interventions targeting children, an increased use of objective assessment measures is observed in the literature (Pang et al, 2017); still, most of the times these measures entail interaction with the treated subjects, e.g. they are asked to wear pedometers or accelerometers. As subjects are aware of being observed, social desirability bias may lead to an inflated response and overestimation of the policy effect. Only two of the reviewed studies applied quasi-experimental methods on observational data: in both studies, trained observers at standardized locations recorded traffic counts (Pang et al., 2017). Heinrich et al. (2011) consider 13 schools, while Bungum et al. (2014) consider 2 schools only. Therefore, there seems to be a scarcity of robust observational studies, especially evaluations of cycling policies targeting children.

Altogether, these findings point out that the estimated policy effect not only depends on the specific intervention and setting, but also on evaluation choices regarding the methodology and the outcome measurement. Most of the existing studies lack external validity and/or are affected by non-negligible biases. These are mostly related to the lack of adequate control and comparison groups. In their systematic review, Möser & Bamberg (2008) consider 141 evaluation studies of soft transport policy measures, and conclude that none of the studies was based on a robust and reliable evaluation design, nor applied statistical significance testing, and most of the studies were based on non-representative samples. A recent review of studies evaluating school-based interventions to promote active commuting classified fourteen out of eighteen studies as low assessment quality, a minor improvement relative to a previous review which classified all evaluations as weak (Chillón et al., 2011; Pang et al., 2017). A more recent review imposed strict criteria to select “studies with strong methodological designs, as these types of studies are the only ones that warrant causal conclusions” (Semenescu et al., 2020). Only experimental and well-controlled quasi-experimental studies were considered, and out of 169 identified studies, 50 had no control group and 13 studies did not report enough information to calculate effect sizes.

In order to obtain credible causal results of the policy impact, our study exploits observational data in a quasi-experimental setting. As already mentioned in Section 1, the additional value of the present study consists in the use of objective measurements as those provided by counters in bicycle lanes, and the estimation of a difference-in-difference (DiD) model controlling for observed confounders, which enables the identification and estimation of the causal effect of the Cycling May intervention in the city of Gdansk. Examples of cycling-related evaluations based on the DiD approach are Kuo et al. (2021), Campbell and Brakewood (2017); Kraus and Koch (2021) and Wang and Lindsey (2019).

3. The intervention

Cycling May is a public campaign aimed at increasing the usage of bicycles, primarily targeting children. The campaign has been developed and promoted by the city of Gdansk, and it has been implemented during the month of May, every year since 2014. By 2019, 47 other Polish cities and municipalities had adopted the initiative.

The primary aim of the campaign is to encourage active transport among pupils in primary schools and kindergartens, their parents and teachers. The initiative is based on a competition, adopting a gamification approach. Every child and teacher receives a sticker for each time that she cycles to school, and there are final prizes for children, classes and schools that are most active. Children are provided with their own travel diary to keep track of bicycle trips, and a class poster allows to record cumulative trips. Awards come in the form of bicycle gadgets for children, organized class excursions, or financial support for the amelioration of schools' cycling facilities. Along with the competition, accompanying measures include school activities to teach good and healthy transport habits. School participation is voluntary, and primary schools and kindergartens must apply to participate to the initiative.

Table 1 displays descriptive information on the Cycling May campaign in Gdansk over time. Since 2015, the number of participants has more than tripled, involving nearly 35,000 individuals in 2019. Each participant makes on average 27 bicycle rides during one month of the campaign, where a bicycle ride is considered as a single home-to-school or school-to-home trip. Table 2**Błąd! Nie można odnaleźć źródła odwołania.** shows targeted groups in 2019 expressed both as absolute number of individuals and as percentage relative to Gdansk population; 7.4 percent of overall Gdansk population participated to the campaign. If we refer only to Cycling May potential participants, the campaign effectively involved six out of ten individuals in the target group (61.3%).

Table 1. Cycling May campaign - numbers in Gdansk

Year	Num. of active participants (thous.)	Num. of registered bicycle rides (thous.)	Avg. number of individual trips (one-way trips)	Num. of participating schools and kindergartens
2014[1]	1.7	n.a.	n.a.	25
2015	10.0	n.a.	n.a.	78
2016	22.3	263.0	11.8	91
2017	26.0	713.0	27.4	123
2018	31.9	846.4	26.5	144
2019	34.6	950.2	27.4	152

[1]In 2014 the campaign was implemented as a pilot test for 2 weeks only, in the following years it lasted for the entire month.
Source: City of Gdansk

Table 2. Cycling May target groups in 2019, Gdansk

Target group	Target population size	Share of Gdansk's population (%)
Kindergarten pupils	16,585	3.5
Kindergarten teachers	approx. 1,300	0.3
Primary school pupils	35,121	7.5
Primary school teachers	approx. 3,500	0.7
Total target individuals	56,506	12.0
Participants	34,615 (61.3% of target)	7.4

Source: Gdansk Statistical Office

4. Data and Methods

4.1. Methodology

The empirical estimation of the impact of Cycling May campaign on bicycle traffic is based on a difference-in-differences (DiD) approach with a control group and panel data. We compare daily bicycle traffic from individual counters in Gdansk – where the intervention was implemented – with bicycle traffic from counters in Lodz, another Polish city not implementing Cycling May. The choice of the control city was guided by several factors: i. the control city must be unexposed to the intervention throughout the period of analysis; ii. daily bicycle traffic data must be available, and not all cities have placed bicycle counters or provide open access to the data; iii. the control city must be comparable to Gdansk.

Lodz is one of the largest cities in Poland, and so is Gdansk (third and sixth largest cities by population size, respectively), and they have similar territorial extension. Gdansk is the capital of the Pomeranian province, a coastal province in northern Poland, while Lodz is the capital of the homonym province, situated in central Poland. Table 3 displays descriptive information about the two cities.

Table 3. Socio-demographic information: Gdansk and Lodz

	Gdansk	Lodz
Population	470,907	690,422
Area [km^2]	262.0	293.3

Unemployment rate [%]	2.3	5.9
Average employment in industry [%]	14.8	33.7
Average gross salary [PLN]	6,154.4	5,174.8
Number of students [thous.]	64.1	74.0
Annual public expenses for transport and communications [m PLN]	822.6	803.3
Length of cycling network [km]	196	166
Bicycle share in modal split [%]	6 (2016)	2 (2014)
Bike sharing system	MEVO	Łódź public bike
time of operation	*2019 (Mar-Oct)*	*2016–2020 (Mar-Nov)*
number of bicycles	*1200*	*1000*
number of users in 2019	*161,253*	*n.a.*
use by tourists [%]	*20.6*	*n.a.*

Data are referred to 2019 unless differently specified.
Data sources: City of Gdansk, 2021; Gdansk Gdynia Sopot Metropolitan Area, 2021; Normal City Phenomenon Foundation, 2021; Statistical Office in Gdansk, 2021; Statistical Office in Lodz, 2021

Our DiD model is estimated through a panel regression models that account for fixed cross-sectional (counter-level) and time effect. The estimated basic model has the following equation:

$$y_{it} = \gamma X_{ct} + \delta CM_{it} + \beta Z_t + \lambda_i + \varepsilon_{it} \tag{1}$$

The dependent variable is the number of bicycles registered by each counter i on day t. X_{ct} are city and time specific variables, Z_t are time specific variables, λ_i are counter-specific fixed effects, ε_{it} is the residual error component. The binary variable CM_{it} refers to the policy and is 1 for May observations from Gdansk counters, and 0 otherwise, so that the coefficient δ is the DiD estimator of the average treatment effect on treated units. This coefficient returns the additional bicycle traffic generated in Gdansk by the Cycling May intervention, after controlling for covariates.

The vector X_{ct} in Eq (1) includes city and time specific control variables that account for specific weather conditions and touristic flows in each city:

$$\boldsymbol{\gamma X}_{ct} = \gamma_1 WindSpeed_{ct} + \gamma_2 Cloudiness_{ct} + \gamma_3 Temperature_{ct} + \gamma_4 Precipitations_{ct} + \gamma_5 Tourists_{cm} + \gamma_6 Bike\ sharing_{ct} \tag{2}$$

Daily average wind speed, cloudiness, temperature and precipitation are considered for each city. The $Tourists_{cm}$ variable refers to the number of tourists in Gdansk and in Lodz. The latter variable is recorded on a monthly basis, and each daily observation *t* is associated with the respective month $m = 1, \ldots, 36$. The binary bike sharing variable controls for the activation of a bike sharing system in Gdansk, starting March 25, 2019[2].

The vector Z_t in Eq (1) contains time specific variables that are common to the treated and control groups, including seasonal factors relevant to commuting, i.e. differences in bicycle traffic by quarter q, day of the week and holidays in Poland[3]. We specify the Z_t component of the model as follows:

$$\boldsymbol{\beta}\, \boldsymbol{Z}_t = \sum_{q=1}^{3} \beta_{1q} Quarter_q + \sum_{d=1}^{6} \beta_{2t} DayofWeek_t \ + \ \beta_3 PublicHolidays_t \\ + \ \beta_4 SummerHolidays_t \tag{3}$$

The counter-specific fixed effects included in the model (λ_i in Eq. (1)) allow to control for all time-invariant differences between bike lanes, e.g. distance from schools, average traffic, etc. By including these fixed effects, we control for any omitted time-invariant factor at the counter level. ε_{it} is an error term that captures any unobserved factor that may affect bicycle traffic and is assumed to have zero mean, conditional on the counter and day.

The DiD approach does not require that the treated and control group are similar in all respects, the key requirement is that the outcome of interest – in our case daily bicycle count – would have the same trend (i.e. move in parallel) in the two groups in absence of the treatment and after conditioning on observed confounding factors (Angrist & Pischke, 2014). This common trend assumption can, and should, be tested in the pre-treatment period. Since the model includes time-varying controls, the common trend assumption between the two groups must be met conditionally on these covariates. In the current application, we test the common trend assumption by comparing the outcomes over those months in which the intervention is not implemented (non-treatment periods), without and with control variables.

The identifying assumption of our model is that there are no omitted factors that have a differential impact on bicycle traffic in Gdansk and in Lodz. In other words, we assume that, after controlling for systematic differences through fixed effects and time-varying city-level covariates (atmospheric conditions, touristic flows and bike sharing activation in Gdansk), in absence of the policy the average outcome in the two cities would be the same.

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[2] A bike sharing system was in place in Lodz for the entire period if analysis (starting in May 2016). We assume that the effect is therefore steady over the entire period.

[3] The binary variable *SummerHolidays* accounts for the months of July and August, and is related to school closure; *PublicHolidays* accounts for national festivities in Poland, i.e. days free of work.

In order to test for the robustness of our findings, we estimate several additional models that differ in term of specification of the dependent variable, functional form and estimation method, i.e. (1) fixed effects panel regression with the natural logarithm of daily bicycle counts as dependent variable (therefore coefficients estimates are to be interpreted as percentage changes in the number of bicycles); (2) panel Poisson regression using absolute number of bicycles, here estimates refer to the difference between the log of expected counts and their exponential function represents the change in the expected number of bicycles (3) Cycling May intervention included as number of yearly participants (rather than a binary variable as in the baseline specification).

A similar DiD model applied to daily bicycle counter data has been used before in the study by Kraus and Koch (2021). While we partially follow their approach, the evaluation of Cycling May campaign has one peculiarity related to the fact that the intervention is repeated regularly over time. This means that there are no unique pre- and post- implementation periods, but treatment periods (the months of May) and non-treatment periods are cyclic. The effect of the policy is observable during the month of May, but there might be a persistence effect in the subsequent period, when schools are still open. To explore such persistence, we check for differential outcomes for the month after the policy (June). A placebo test is also performed: this falsification test is performed by randomly drawing observations about three counters in Gdansk and three counters in Lodz as a new treatment group, and a different subset of observations relative to three counters in each city as a new control group. In this way observations in the "real" treatment and control groups should balance, and the effect of Cycling May should be close to zero. Results of estimated model, robustness checks and placebo test are displayed in Results Section.

4.2. Data

Our data cover a three year period, from the beginning of September 2016 to the end of August 2019. Cycling May campaign was implemented in Gdansk every May in each year between 2017 and 2019.[4] In 2020 the intervention was not in place because of the ongoing COVID-19 restrictions. The following year the intervention was regularly implemented, but we decided to exclude these observations from the analysis. The pandemic has significantly influenced both the work patterns, transport choices and behaviour of

[4] The European Cycling Challenge (ECC), a different cycling promotion campaign, was implemented in May 2017 in both cities with less than one thousand participants in Lodz and around 3 thousand participants in Gdansk. Participation to the ECC initiative in Gdansk is considerably lower than participation to Cycling May (around 26,000 participants in the same year). Therefore, we expect a negligible increase in bicycle traffic due to the ECC campaign, and at any means the relative ECC effect in the two cities is assumed to be comparable, and thus to cancel out.

individuals (see e.g. Anke et al., 2021; Rafiq et al., 2022); for this reason, the effect of the policy in 2021 might be very different from the pre-pandemic effect, and it could therefore confound the average annual effect estimated by our model[5]. On top of that, at the beginning of 2020 a new important road was opened for cyclists in Gdansk, linking poorly connected residential districts with the already existing cycling network and changing bicycle traffic distribution in the city, creating a disruption in the data historical comparability.

The raw data include daily bicycle counts from 26 counters in Gdansk and 9 counters in Lodz (see Figure A1 and Figure A2 in the Appendix) (City of Gdansk, 2021; City of Lodz, 2021). The counters in both cities operate using induction loop technology and provide permanent and automated bicycle counting.[6] Initial data validation is performed by the responsible city units, e.g., there could be situations of incorrect readings due to magnetic interferences, outages due to power exhaustion or other minor problems. These kinds of errors are identified, and corresponding data are rejected and considered as missing data points. Additional data cleaning was conducted within this research: observations from three counters in Gdansk were excluded because they were installed after the beginning of our period of analysis; observations from two counters in Lodz were also excluded from the analysis because of missing data (likely due to counters technical problems). Therefore, our dataset includes bicycle counts from 30 counters (23 in Gdansk, 7 in Lodz) over a period of 1.095 days, resulting in 32.850 observations.

The daily bicycle traffic at the counter level is our outcome of interest. Figure 1 shows the average (across counters) number of daily bicycles counts in the two cities, by month and year. The trend is similar, except for the months from May to August, when the bicycle traffic in Gdansk is relatively more intense. The introduction of the bike sharing system in Gdansk in April 2019 produces a clear increase in bicycle traffic.

[5] The data from 2021 suggest that the intervention was less popular – the number of participants fell to 31,498 (-9% compared to 2019) and the average number of trips was significantly lower than before pandemic (21 trips per participant in 2021 compared to approx. 27 trips per participant in the analysed period of 2016-2019).

[6] Bicycles passing over the loop are detected based on electromagnetic signal between bicycle and the detector. The technology is commonly used to measure bicycle traffic at bike lanes and shared paths, largely because of its insensitiveness to inclement weather conditions and high reliability (99% as reported by Ozan et al. (2021)).

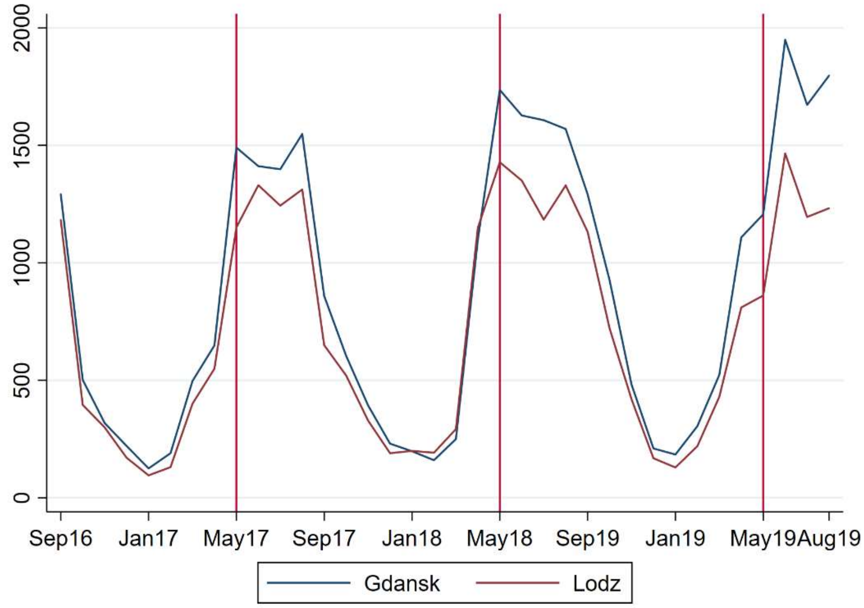

Figure 1 – Average number of bicycle counts by city and month

A possible explanation for the gap in bicycle traffic between the two cities during the summer is related to the touristic flow. Since Gdansk is situated by the sea, tourist numbers are likely to escalate during the summer, and one out of five bike rentals is from a tourist (20.6%; Gdansk Gdynia Sopot Metropolitan Area, 2021), not counting bike rentals from hotels and private companies. Thus, the use of bicycles by tourists may contribute to the higher number of bicycles registered by counters during summer season in Gdansk. Figure 2 displays the monthly number of tourists in the two cities, and clearly shows that Gdansk is characterized by highly seasonal tourism, while touristic flows in Lodz are more stable across different seasons and during the period considered. Accordingly, the number of tourists could become a good control in the model, accounting for the different bicycle traffic during the summer.

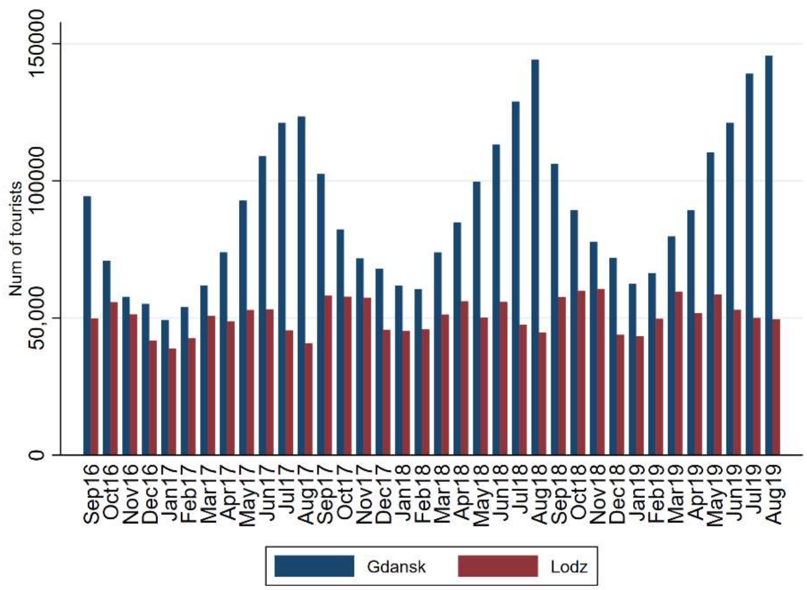

Figure 2 - Number of tourists, trend by month and city (Statistical Office in Gdansk, 2021; Statistical Office in Lodz, 2021)

Other covariates acting as control factors in the panel DiD model refer to daily weather data obtained from meteorological stations located in Gdansk and Lodz, close to the central areas, regarding average temperature, average wind speed, average cloudiness and total daily precipitation (Polish Institute of Meteorology and Water Management, 2021). Table 4 displays descriptive statistics for the outcome variable and explanatory variables, averaged over the period of analysis. Lastly, we control for the period in which bike sharing was active in Gdansk, that is after April 2019.

Table 4. Descriptive statistics of explanatory variables in treatment and control groups

	Mean	*Standard Deviation*	*Minimum*	*Maximum*
Gdansk				
Sum of daily bicycles	20,291	15,316	518.7	55,863
Average daily bicycles per counter	882.2	665.9	22.6	2,429
Average daily wind speed [m/s]	4.0	1.8	0.3	12.3
Average daily overall cloudiness [octants]	5.6	2.2	0	8
Average daily temperature [°C]	8.5	7.9	-12.3	25.9
Daily sum of precipitation [mm]	1.9	5.2	0	99.8
Monthly number of tourists using accommodation [thous.]	89.5	27.1	49.3	145.6
Lodz				
Sum of daily bicycles	5,045	3,830	184	14,456
Average daily bicycles per counter	720.7	547.2	26.3	2,065
Average daily wind speed [m/s]	3.3	1.551	0.900	10.80
Average daily overall cloudiness [octants]	5.4	2.148	0	8
Average daily temperature [°C]	9.5	8.528	-16.70	28.90
Daily sum of precipitation [mm]	1.7	4.690	0	46
Monthly number of tourists using accommodation [thous.]	50.7	5.939	38.84	60.61

4.3. Testing the common trend assumption

We test the common trend assumption outside the intervention periods – i.e. excluding observations in the month of May – while allowing for differential linear trends in the two cities.

Table **5** shows results of panel regression models estimated on daily bicycle counts as dependent variable: model (1) checks for the common trend assumption over time without controlling for any other exogenous factor and model (2) controls for the time-varying effect of covariates. Model 1 results in a significant differential trend in bicycle traffic in the two cities, which becomes insignificant when controlling for exogenous factors. Moreover, after controlling for covariates the common trend becomes smaller and negative, meaning that the positive trend captured by model (1) can be explained by other exogenous factors. Therefore, the common trend assumption holds after controlling for seasonality, number of tourists, day of the week, holidays, atmospheric conditions, and activation of bike sharing in Gdansk, and we control for these factors in the DiD model.

Table 5 – Check for common trend in non-treatment periods, without controls (1) and including controls (2)

	(1)		(2)	
Trend	11.92***	(0.97)	-2.48***	(0.69)
Trend # Gdansk	8.20***	(1.11)	0.03	(0.85)
Wind speed			-32.96***	(1.75)
Cloudiness			-53.65***	(1.60)
Temperature			42.12***	(0.73)
Precipitation			-13.94***	(0.62)
Number of tourists (thous.)			5.51***	(0.25)
Monday			132.94***	(11.52)
Tuesday			172.90***	(11.55)
Wednesday			167.49***	(11.60)
Thursday			154.49***	(11.53)
Friday			94.97***	(11.52)
Saturday			-22.43*	(11.51)
Public holiday			-150.77***	(18.02)
Summer holiday			110.95***	(13.70)
Quarter=2			209.58***	(13.81)
Quarter=3			10.24	(16.53)
Quarter=4			-48.32***	(9.13)
Bike sharing Gdansk			162.29***	(13.91)
Constant	483.29***	(9.18)	341.95***	(20.76)
N		30,060		30,060
Log likelihood		-242,727		-231,415

Standard errors in parentheses. * p<0.1; ** p<0.05; *** p<0.01

5. Results

Results of the DiD model are displayed in

Table **6**. Model (a) is a panel OLS regression with fixed effects and standard errors clustered by bicycle counter, with dependent variable being the number of daily bicycles per counter. According to the estimated model, the Cycling May campaign in Gdansk increases bicycle traffic by nearly 158 bicycles per day per counter, ceteris paribus.

Table 6 – DiD estimates

Model (a)	Coefficient	Standard error
Wind speed	-33.81***	(4.61)
Cloudiness	-59.84***	(8.35)
Temperature	43.73***	(5.67)
Precipitation	-14.48***	(2.17)
Number of tourists (th.)	5.04	(3.16)
Monday	134.03**	(53.88)
Tuesday	173.72***	(55.92)
Wednesday	169.22***	(53.14)
Thursday	150.53***	(49.97)
Friday	84.44*	(48.97)
Saturday	-20.03	(14.14)
Public holiday	-128.79**	(48.64)
Summer holiday	116.45***	(40.69)
Quarter=2	210.38***	(45.14)
Quarter=3	6.52	(56.04)
Quarter=4	-44.73**	(17.34)
Bike sharing Gdansk	69.05***	(21.63)
Cycling May	*158.36****	*(36.86)*
Constant	-33.81***	(4.61)
Counter FE	Y	
N	32,850	
LL	-253695	
R squared	0.70	
AIC	507426	
BIC	507578	

* p<0.1 ** p<0.05 *** p<0.01

The direction of covariate effects follows expectations. Atmospheric conditions, day of the week and period of the year significantly affect bicycle traffic. Cloudiness, wind speed and precipitations negatively affect bicycle traffic, while more bicycles are observed as temperature increases. Higher bicycle traffic is observed during weekdays compared to weekends, and less bicycles are counted during public holidays, meaning that bicycles are a way of transport mainly used by commuters, compared to the use for leisure activities. During spring and summer holidays, more bicycles are observed; the implementation of bike sharing system in Gdansk produced a significant increase in bicycle traffic.

Table 7 displays estimates from alternative model specifications, to test the robustness of results. Model (b) takes the natural logarithm of daily bicycle counts; model (c) is a Poisson regression using bicycle absolute count as dependent variable. Besides the average effect produced by the Cycling May intervention, we explore the effect in relation to the number of registered participants in model (d), which can be used as a proxy of the “intensity” of the treatment. The resulting coefficient can be interpreted as the average increase in overall daily number of bicycles per counter generated by each registered participant.

If we consider the average percentage change in model (b), a 18% increase in bicycle traffic is estimated; finally, the coefficient estimate from model (c) suggests a 14% increase in the expected number of bicycles when the intervention is in place. Results of model (d) indicate that there are on average additional 4.5 bicycle per day per counter per thousand of participants; considering the 23 counters and the participation of 34.6 thousands of individuals, this corresponds to a total of nearly 3.5 thousand more bicycles per day in Gdansk during policy implementation periods, which is consistent with results from other models (e.g. 158 more bikes * 23 counters= 3,634 daily increase).

Table 7 – DiD estimates – alternative specifications

	(b)		**(c)**		**(d)**	
Cycling May	*0.18****	*(0.012)*	*0.14****	*(0.010)*		
Participants (th.)					*4.50****	*(1.032)*
Counter FE	Y		Y		Y	
N	32,727		32,850		32,850	
LL	-18617		-1550739		-253709	
R squared	0.88		0.90		0.70	
AIC	37271		3101516		507455	
BIC	37422		3101676		507606	

Standard errors in parentheses; * p<0.1 ** p<0.05 *** p<0.01. Covariates estimates not shown.
Percentage increase (i.e. Exp(beta)-1), Pseudo-R squared and Log pseudo-likelihood reported for model (b).

Results are consistent across the various specifications and indicate a significant increase in bicycle traffic in Gdansk attributable to Cycling May campaign. If one relates the estimate of the absolute number of additional bicycles (model a) to the average bicycle traffic in Gdansk over the three years of our sample (882 bicycles per counter per day), the estimated impact of the campaign is again 18%, which matches the result obtained from model (b).

Estimates displayed in Table 8 refer to the persistence effect of Cycling May in the days following the end of the initiative (model e). The stock variable represents the average daily traffic for each counter in the past 30 days, therefore the interpretation of the stock coefficient relates to a persistence effect, i.e the relationship between the traffic over the previous month and the traffic of the considered day. The interaction of stock, month of June and city of Gdansk reveals the difference between the average persistence over the whole sample, and the specific (additional) persistence in June in Gdansk; the negative and small, but highly significant, coefficient means that in the month after the implementation of the Cycling May campaign there is a decrease in persistence, in other words the increase in bicycle use in May is not sustained after the policy ends.

Table 8 – DiD estimates - Cycling May persistence

Model (e)	Coefficient	Standard error
Participants (th.)	4.10***	(0.85)
Stock	0.83***	(0.03)
Stock # June # Gdansk	-0.02***	(0.01)
Counter FE	Y	
N	31,950	
LL	-237242	
R squared	0.84	
AIC	474524	
BIC	474691	

Standard errors in parentheses; * p<0.1 ** p<0.05 *** p<0.01
Covariates estimates not shown.

Table **9** reports additional robustness checks. In model (f) the dependent variable is the average daily bicycle count by city rather than by counter, and confirms the positive and significant effect of Cycling May. Including differential linear trends (model g) does not sensibly change the estimated effect of Cycling May, compared to model (a). In model (h), we account for city-specific quarterly differences in bicycle traffic for each year, and again we report consistent findings.

Table 9 – DiD estimates, robustness checks.

	(f)		(g)		(h)	
Cycling May	*164.77***	*(10.02)*	*153.94****	*(34.19)*	*146.80****	*(18.63)*
Monthly trend			-3.25**	(1.52)		
Monthly trend # Gdansk			0.78	(1.42)		
Quarter1					142.94	(109.69)
Quarter2					25.82	(152.61)
Quarter3					58.76	(168.15)
Quarter4					284.01***	(84.56)
Quarter5					85.67**	(40.98)
Quarter6					-20.62	(134.42)
Quarter7					96.82	(169.56)
Quarter8					312.30***	(82.61)
Quarter9					47.53	(44.47)
Quarter10					7.29	(113.96)
Quarter11					9.04	(153.67)
Quarter12					122.62***	(42.59)
Quarter1 # Gdansk					149.84	(132.90)
Quarter2 # Gdansk					207.81	(124.71)
Quarter3 # Gdansk					220.65	(131.20)
Quarter4 # Gdansk					167.75**	(71.18)
Quarter5 # Gdansk					104.89**	(47.02)
Quarter6 # Gdansk					177.58	(122.66)
Quarter7 # Gdansk					139.32	(153.30)
Quarter8 # Gdansk					156.24	(111.05)
Quarter9 # Gdansk					93.93	(66.78)
Quarter10 # Gdansk					177.08*	(103.65)
Quarter11 # Gdansk					186.84	(138.54)
Quarter12 # Gdansk					52.99	(39.80)
Counter FE			Y		Y	
City FE	Y					
N	2,190		32,850		32,850	
LL	-14826		-253676		-253622	
R squared	0.88		0.70		0.70	
AIC	29688		507395		507323	
BIC	29791		507571		507650	

Standard errors in parentheses. * p<0.1 ** p<0.05 *** p<0.01. Covariates estimates not shown.
Quarters are three month-periods (Jan-Mar, Apr-June, Jul-Sep, Oct-Dec), except Quarter1= September 2016; Quarter13=July and August 2019. Quarter13 is the reference period.

Finally, we run a placebo test with new treatment and control groups made as a mixture of randomly drawn observations from counters in the treatment and control groups. We expect the DiD estimator of the Cycling May intervention to be close to zero. Table 10 shows that the estimated coefficient is not significantly different from zero, which supports our identification strategy.

Table 10 – Placebo test

Model (i)	Coefficient	Standard error
Cycling May	-6.56	(16.73)
Counter FE	Y	
N	13,140	
LL	-95608	
R squared	0.84	
AIC	191255	
BIC	191397	

Standard errors in parentheses; * p<0.1 ** p<0.05 *** p<0.01
Covariates estimates not shown.

6. Discussion and conclusion

In this paper we investigate the effectiveness of the Cycling May campaign in Gdansk on the overall bicycle traffic registered by traffic counters installed on the city cycling network. The Cycling May campaign is the biggest cycling promotion campaign in Poland and involves tens of thousands of participants each year (34,615 in 2019) who actively commute to and from primary schools and kindergartens.

The present evaluation applies a quasi-experimental design on observed number of bicycles in targeted and control groups, controlling for potential confounders, such as atmospheric conditions, day of the week, holidays, season of the year and touristic flows. The implementation of a longitudinal panel data analyses is encouraged by Richter et al. (2011) as a method that allows to draw valid conclusions on the effectiveness of soft transport policies.

Results from the difference in difference model clearly show that bicycle traffic responds to the intervention. On average, we ascribe an additional 159 bicycles per counter and day to the Cycling May campaign, which represents a 18% increase in Gdansk's bicycle traffic on cycling network during May.

Our results support to the general conclusion by Semenescu et al. (2020), Ogilvie et al. (2004) and Möser & Bamberg (2008) that soft transport policy interventions significantly contribute to behavioural changes among participants while the intervention is in place. However, when investigating the impact in the days following the Cycling May campaign, we find that its positive effects are not maintained. This finding suggests that individuals that used the bicycle in May return to their usual mode of transport in June, thus there is no evidence that the policy is effective in changing people behaviour in the long term.

This result is in line with previous studies (Bungum et al., 2014; Diniz et al., 2015; Höchli et al., 2019). Further research is needed on the reasons for the lack of long-term effects of soft transport policy interventions. Considering our case, we argue that the gamification approach, which is inherently based on some kind of competition, loses its power on behavioural change when the competition – and relative reward

– dimension is removed. In other words, the behavioural change is motivated by an external cause, i.e. winning a prize, and not by an actual change in pupils' intrinsic motivation to use the bicycle. However, there are other factors to consider, most importantly we should bear in mind that primary school students are not in charge of commuting decisions and must rely on their parents' choices. Parents could be motivated to change their habits for a short period of time due to the intervention, but may switch back to their usual mode of transport because of overarching time constraints and convenience motives. Moreover, we must consider that the school period usually ends on the third or fourth week of June, leading to a drop in the number of commuters to school.

Therefore, a reflection should be made on the gamification approach in relation to the specific policy aim. If the objective is to make children familiarize with active transport modes, induce positive attitudes towards cycling, and have a short-term increase in usage of the bicycle, this and other studies show that the gamification approach can be a powerful instrument. If, on the other hand, the intervention aim is to induce a long-term change in commuting habits, more attention should be devoted to the attitudes and needs of parents and households altogether, also considering differences among households, e.g. number and age of children in the households, distance from the schools and workplaces, who is the person that usually shepherd kids to school.

Although the results of the research indicate only a short-term positive effect of the campaign, the overall aim of this type of activity is to educate users (especially children) that one can commute to school, work or other purposes by bicycle, that the bicycle is not just for fun and recreation, and may be an alternative to a car or public transport. This indirect and perhaps not immediate goal may bring results in terms of building positive attitudes in children, and could show its implications over the future years.

Cycling May campaign is a large-scale campaign and students and their families are highly engaged. We argue that our results can be extended to other large-scale campaigns using similar instruments, e.g. a combination of gamification and education measures. However, we may expect that a pre-requisite for the effectiveness of any intervention of this kind is the availability of an adequate cycling infrastructure. The bicycle infrastructure in Gdansk is extensive and largely consists of bicycle paths separated from car traffic. Without a developed cycling infrastructure, it is unlikely that parents would allow children to commute by bike, given the danger of cycling in car lanes, especially for children. Therefore, policy makers that seek to encourage a shift in transport modes among commuters can rely on relatively inexpensive soft transport policies to promote active transport, but should first implement infrastructure improvements for creating walking and cycling friendly cities.

The present study suffers from some limitations. We have no information on modal shift among campaign participants, i.e. whether their previous transport mode was car, public transport or walking. Hence, we cannot provide evidence related to car usage reduction. Moreover, while the use of observational data reduces potential biases on bike usage frequency coming from self-reported data, it also does not allow to gain information on attitudes, beliefs and habits of participants, and therefore we could not measure whether attitudes towards cycling changed due to the intervention.

A further limitation of our study is represented by the lack of information on secondary outcomes, such as the environmental benefits (reduction of pollution due to switch from car to bicycle) and health benefits related to increased physical activity. Given that the intervention is explicitly targeting children, and is explicitly aimed at promoting long-term attitudes towards healthier and environmentally-friendlier transportation, a proper assessment of the ultimate benefits is at least challenging, and beyond our scopes. While it is not possible to report a reliable assessment of the cost-effectiveness of the intervention, the Cycling May campaign requires a relatively low budget (around 110 thousand Euro in 2017, 155 thousand Euro in 2018, and 194 thousand Euro in 2019 for implementation in the city of Gdansk), which should justify the intervention even based on the mere estimate of a temporary increase in bike traffic.

Hence, further research is needed to gain insights on the ultimate effects of active transportation policies, such as change in health and environmental outcome, as well as habit formation for interventions targeting children. While few studies take into account these secondary outcomes (see Keall et al., 2018), we believe that understanding the effects of soft transport policies on the environment and people health is critical to face important challenges of our daily life, such as increased pollution and rising obesity. Furthermore, an interesting extension would require the combination of observational data with self-reported information. This would allow to gain a deeper insight into the mechanisms that induce behavioural changes and to assess whether the intervention stimulate the shift from car to active transport.

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Appendix

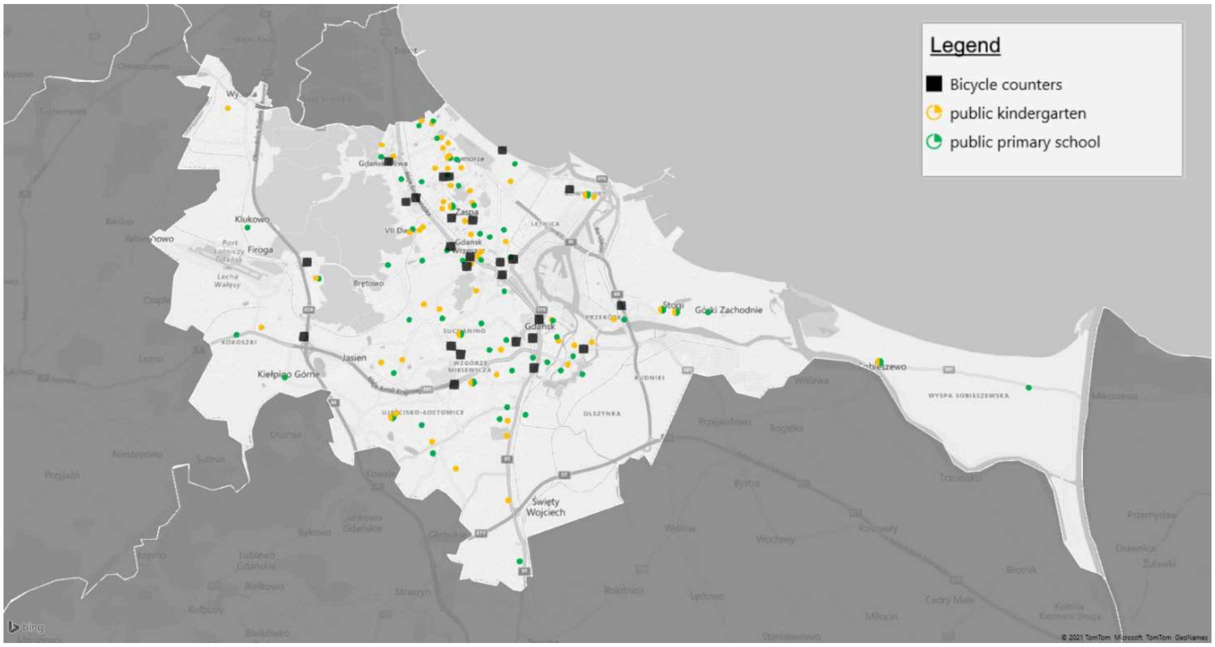

Figure A1. Location of bicycle counters in Gdansk

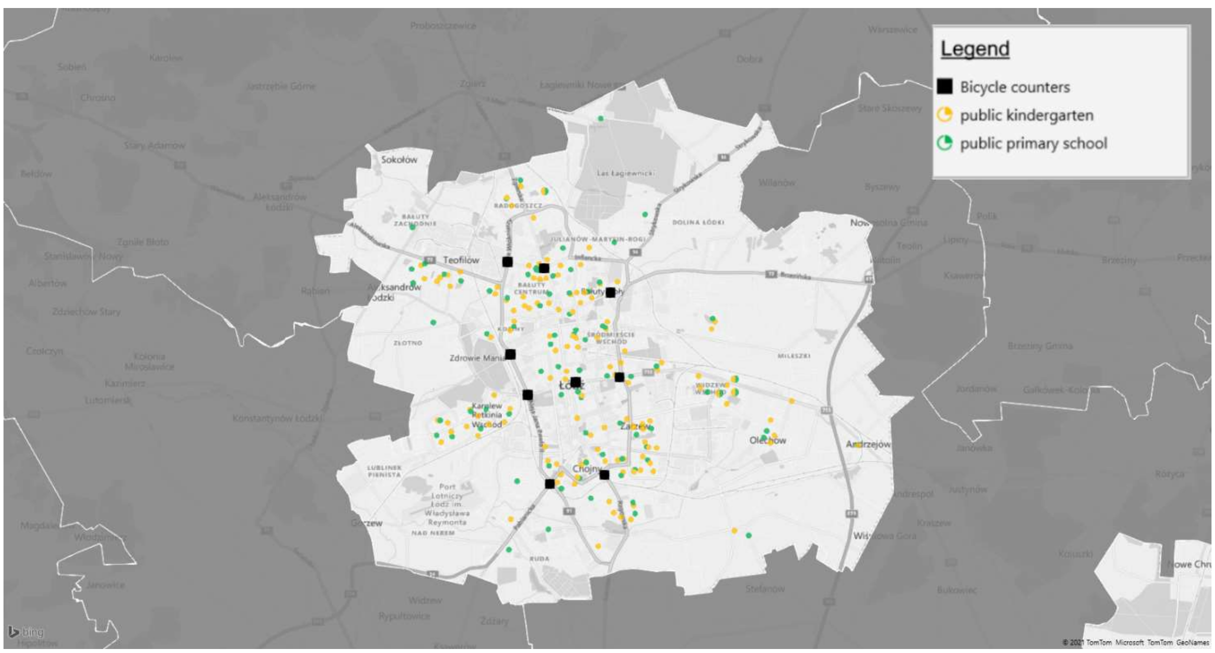

Figure A2. Location of bicycle counters in Lodz