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Combining convex regression with the regression discontinuity design: Effectiveness of e-scooter providers during the Covid-19 lockdown

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ABSTRACT

The efficiency literature has only recently begun to address endogeneity and causal inference in frontier estimation. Most previous studies combine efficiency analysis with causal inferences using a two-stage estimation strategy, hence not properly addressing correlation between efficiency and treatment. This paper proposes a one-stage approach that combines a semi-nonparametric estimator subject to shape-constraints with the quasi-experimental regression discontinuity design. The proposed method enables joint estimation of the impacts of contextual factors and a non-parametric production frontier. Building on recent methodological developments within the literature on regression discontinuity design, the current paper develops strategies for estimation, bandwidth selection and inference for both average and heterogenous treatment effects. The novel methodology is applied for analyzing the reopening of Norway after lockdown using the Regression Discontinuity in Time design, considering both *average* and *firm-specific* treatment effects. Empirical analysis of the novel e-scooter markets in the cities Oslo and Drammen indicates that while the average performance of e-scooter providers was unaffected by the reopening of Norway during the Covid-19 pandemic, operators are heterogenous with regards to both effectiveness and responsiveness. While the empirical analyses provide mixed evidence that lockdown policies affect transport operator performance, they offer important insights into the benefits of accommodating heterogenous policy impacts in assessment of diverse and volatile industries.

1. Introduction

Modeling operational conditions and practices that influence productive efficiency of firms and other decision-making units has attracted considerable research interest in the past decades (e.g., Simar & Wilson, 2007; Banker & Natarajan, 2008; Johnson & Kuosmanen, 2011, 2012). The conventional approach is to examine correlation between the so-called z-variables and efficiency of the firm. However, statistical correlation does not necessarily imply a causal relationship. While causal inference is deemed paramount in many other disciplines, it has only recently begun to attract attention in the efficiency literature: Building on causal inference methods in economics, recent studies such as Zhang et al. (2020), D'Inverno et al. (2021), Mergoni and De Witte (2022) and Badunenko et al. (2023) stress the importance of causal inference in efficiency measurement.

While several studies have aimed to combine productivity and efficiency analysis with the regression discontinuity design (RDD), most of them rely on a two-stage procedure, implementing conventional efficiency analysis in the *first stage*, and subsequently applying the RDD approach in the *second stage* using results from the first stage as the dependent variable. As noted by Mergoni and De Witte (2022), the two-stage approach does not appropriately address the correlation between efficiency and the treatment indicator. We argue that such a two-stage estimation approach is subject to similar endogeneity bias as the two-stage Data Envelopment Analysis or DEA for short (see Johnson & Kuosmanen, 2012). As a result, the treatment effects estimated using a two-stage procedure are likely biased, which can lead to misguided policy recommendations. In addition, the two-stage estimation strategy is also contingent on a strong separability assumption (see Daraio et al., 2018), which implies that the treatment only affects efficiency, but not the production technology. In our opinion, this could be an unrealistic assumption in the context of policy interventions.

To circumvent these problems, this paper proposes a one-stage approach that combines efficiency analysis and RDD. More

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specifically, we combine a flexible semi-nonparametric estimator subject to shape-constraints – known as convex regression – with the quasi-experimental RDD. Similar to the widely used DEA, convex regression and its variants such as Convex Nonparametric Least Squares (CNLS; Kuosmanen, 2008) and Stochastic Nonparametric Envelopment of Data (StoNED; Kuosmanen & Kortelainen, 2012) allow one to estimate frontier production and cost functions in an axiomatic, non-parametric fashion, but the convex regression approach can also accommodate random noise. Using state-of-the art methods in RDD, we define the proposed RDD-CNLS approach both for average and heterogenous treatment effects. We further demonstrate how the proposed methodology can be applied to decompose the treatment effect into contributions of frontier and efficiency changes.

We apply the new method to analyze how exogenous demand shocks caused by Covid-19 influenced the effectiveness of e-scooter providers using a Regression Discontinuity in Time (RDiT) design. We investigate the effectiveness of eight e-scooter providers in the Norwegian neighboring cities Oslo and Drammen from January 2019 to August 2021. This research agenda targets research gaps in the literature on transport economics, where – to our knowledge – no previous study has investigated the effectiveness of e-scooter operators.

Compared to conventional approaches for analyzing demand uncertainty and normal or anticipated fluctuations in demand (e.g., Simar & Wilson, 2007; Tovar & Wall, 2014; and Chambers & Serra, 2019), the current study investigates the impact of *demand shocks* on service effectiveness. This is essential for understanding the resilience of operators to rapid changes in market conditions, which in turn is crucial for determining the responsiveness and scope for mode substitution in the short run and the economic survival of modes and transport providers in the long run. Our study can further be viewed as an empirical contribution to the literature on deregulation of public transport (see e.g., Dementiev and Han (2020) for an overview).

The proposed RDD-CNLS approach can effectively utilize a high-resolution panel dataset comprising e-scooter operators to estimate *firm-specific* treatment effects. By drawing on recent developments in RDD, our study contributes to the emerging research field on estimation and inference of heterogenous treatment effects. The empirical results suggest that limiting attention to the average treatment effect might mask heterogenous responses to a treatment in a volatile market with heterogenous agents.

The paper is organized as follows: Section 2 provides context regarding the RDD approach while Section 3 presents the methodology. Data are summarized in Section 4 and Section 5 presents our empirical investigations, before we draw our conclusions in Section 6.

2. Primer on RDD

2.1. Literature review

Our dataset involves few decision making units but a long time series. As all decision making units face the same treatment shock, the conventional difference-in-differences approach is unsuited. We instead exploit long time series with high resolution (i.e., daily) data and the methodology associated with the RDD (introduced by Thistlethwaite & Campbell, 1960, cf. Lee & Lemieux 2010 for a review), using proximity in time to the demand shock to study treatment effects.

We combine RDD with shape-constrained nonparametric regression, referred to as CNLS. Such combinations of RDD and other estimation approaches are seldom carried out in the literature. One notable exception is Soland et al. (2022), who provide user guidance for how RDD could be implemented in the structural equations modeling framework.

In the standard RDD setting, treated units are often compared to control units in a cross-sectional setting where the running variable can be any continuous variable (such as age or wealth). Regression discontinuity in time (RDiT) is a specific application of the broader RDD setting where the running variable is time, and the cutoff is a specific policy or intervention date (cf. Hausman & Rapson 2018 for a review). Both RDD and RDiT identify causal effects by observing a discontinuity in an outcome variable at a known threshold, but RDiT focuses on treatment effects around a temporal cutoff rather than a spatial or covariate-based cutoff.

Upon publishing our paper, we became aware of the recent working paper by Verma et al. (2025) that combines efficiency analysis with RDiT (in this case using DEA). The authors assess the impacts of COVID-19 on hospital efficiency and quality. A Regression Discontinuity Design in Time has previously been applied in connection with the COVID-19 pandemics in several applications (Bakolis et al. 2021; Liu et al. 2021 and Jung 2025).

Fixed effects could be used in standard RDD applied to panel data (cf. e.g. Lee & Lemieux 2010), but the fixed effects seem even more relevant for RDiT studies, where the data typically has a panel data structure. Yet, exploiting the fixed effects framework is not in focus within the RDiT literature, although Hausman and Rapson (2018) briefly discuss this methodological combination. In context of unobservables correlated with time, they argue that covariates typically play a larger role in cross-sectional RDDs. They further note that biases may occur even with covariates included, inter alia in relation to overfitting.

Heterogenous treatment effects constitute a novel contribution of our investigation, as providers of e-scooters are likely to be affected differently by – and respond differently to – re-openings after corona-restrictions. As the conventional RDD framework does not follow the same units before and after a treatment shock, less attention has been placed on heterogenous treatment effects in the RDD literature, but with some exceptions. Kawaguchi et al. (2017) consider heterogenous treatment in their RDD study of impacts of reduced standard hours on labor costs and job creation. Hsu and Shen (2019) propose tests for heterogenous treatment in both sharp and fuzzy RDD.

The prominent study by Becker et al. (2013) investigates how the impulses of regional transfers on growth and investments depend on absorptive capacity. Becker, Enger and von Ehrlich apply heterogeneous treatment effects in their RDD setup, as the authors believe regions' absorptive capacity vary. They derive a heterogeneous local average treatment effects estimator for the general scenario with multiple thresholds and interaction variables that affect the treatment effect's magnitude, allowing for a fuzzy treatment assignment mechanism. Among other RDiT studies on heterogenous treatment effects, Grout et al. (2011) study land-use regulations and property values in Portland, Oregon. They estimate region-specific treatment effects, splitting their sample of regions into sub-regions and then applying the standard one-dimensional RDD approach. Hidano et al. (2015) utilize an RDD design with heterogenous treatment in studying information about seismic hazard risk in Tokyo's property market.

The most common approach for considering heterogenous treatment effects in empirical RD analysis is semi-linear local regression with covariate interactions (Calonico et al., 2025). Despite its use for empirical investigations, there has until recently been a shortage of formal methods for heterogenous treatment effects in RDD. In their recent contribution, Calonico et al. (2025) develop theory-based tools for RDD with heterogenous treatment effects. Their state-of-the-art contribution is utilized herein to demonstrate the virtues of accommodating heterogenous treatment effects in volatile markets comprising diverse suppliers.

Another central aspect of the RDD and RDiT literatures is bandwidth selection. Regarding the kernel selection, uniform and triangular kernels constitute the conventional choices. The literature provides some advice and tests on optimal bandwidths based on explanatory power (e.g., Imbens & Kalyanaraman 2012 for RDD and Hausman & Rapson 2018 for RDiT).

Finally, it is worth mentioning that some previous studies combine RDD and efficiency analysis. They mainly build on non-parametric techniques (e.g., Zhang et al. 2020; Agasisti et al. 2021; and Zhuo et al. 2022), but RDD has also been applied together with stochastic frontier analysis (e.g., Johnes & Tsionas 2019). D'Inverno et al. (2021) is among the first studies to stress the importance of causal inference in efficiency measurement. Their approach combines the concept of program efficiency with RDD using *deterministic* DEA. Recently, Badunenko et al. (2023) combine RDD with a 4-component *parametric*, Stochastic Frontier Analysis (SFA) model to estimate the causal impact of a policy intervention. It is well known that an inherent shortcoming of the DEA model is its failure to consider random variations in data, i.e., regards any deviation from the production frontier as technical inefficiency. SFA, on the other hand, accommodates random noise, but requires the selection of a functional form for the cost or production function to be estimated. Our paper advances the studies by D'Inverno et al. (2021) and Badunenko et al. (2023) by combining the RDD method with a *nonparametric, stochastic* frontier model, thus combining the best features of DEA and SFA models. Moreover, we decompose treatment effects into frontier and effectiveness change effects and compare average and firm-specific treatment effects.

2.2. RDiT design

Following Imbens and Lemieux (2008), we denote by $O_{it}(0)$ the outcome for operator i in period t *without* treatment, and by $O_{it}(1)$ the corresponding outcome *with* treatment. The treatment effect is consequently $O_{it}(1)$- $O_{it}(0)$, which cannot be identified directly because both states cannot occur simultaneously.

In the current context, *treatment* (i.e., Covid policy measures) is implemented at a given point in time, making the RDiT design a relevant identification strategy. Herein, we consider a *sharp* RDiT design where all units (i.e., consumers and scooter operators) are subject to identical treatment in each period. Let t_0 denote the time of an intervention. The average causal effect of the treatment can consequently be defined (see Imbens & Lemieux, 2008):

$$\lim_{t\downarrow t_0} E[O_{it}|t_{it}=t] - \lim_{t\uparrow t_0} E[O_{it}|t_{it}=t] \tag{1}$$

which approximates the treatment effect τ at t_0:

$$\tau = E[O_{it}(1) - O_{it}(0)|t_{it}=t_0] \tag{2}$$

A practical method for estimating treatment effects is local linear regression (see Fan & Gijbels, 1996). It enables fitting a linear regression on both sides of t_0. Let l denote the "left side" regression (i.e., prior to treatment) and let r denote the "right side" regression (i.e., after treatment). Let h denote the selected *bandwidth* (e.g., the number of days used for each of the two local regressions, considering identical bandwidths before and after treatment). Throughout, we will apply the uniform kernel for the RDiT analysis. In this case, for the simple approach where the assessment of treatment effect does not take covariates into account, the local linear RDiT approach can be defined (see e.g., Section 4.2. in Imbens & Lemieux, 2008):

$$\begin{aligned} &\min \sum_{i=1}^{I} \sum_{t_o-h<t<t_o}^{T} \left(O_{it} - \mu^l - \kappa^l(t-t_o)\right)^2 \\ &\min \sum_{i=1}^{I} \sum_{t_o\le t<t_o+h}^{T} \left(O_{it} - \mu^r - \kappa^r(t-t_o)\right)^2 \end{aligned} \tag{3}$$

The conditional means $E[O_{it}(0)|t_{it}=t_0]$ and $E[O_{it}(1)|t_{it}=t_0]$ are in this case given by parameters (i.e., constant terms) μ^l and μ^r, respectively, and the average treatment effect (ATE) is thus estimated as ATE $=\widehat{\tau} = \widehat{\mu}^r - \widehat{\mu}^l$.

3. Combining convex regression with RDD

In this section, we adapt the RDiT design to disentangle impacts of Covid lockdown measures on fleet choices and transport effectiveness. We first outline the convex regression approach and the endogeneity problems associated with the two-stage estimation strategy, before introducing a new one-stage estimator that combines convex regression with the RDD.

Before proceeding, it is worth to briefly clarify the notions of efficiency and effectiveness in the context of transport performance. Georgiadis et al. (2014) describe efficiency as the relationship among inputs and outputs, while effectiveness concerns the relationship among inputs and transport demand (operational effectiveness) and between service outputs and transport demand (service effectiveness). As part of their extensive review of the transport benchmarking literature, Daraio et al. (2016) discuss the distinction among supply side variables used for efficiency assessment and demand side variables used for effectiveness assessment. With reference to the efficiency analysis literature, they point out that the use of demand side measures is problematic since these concern factors that are not under the control of the transport provider. However, as stakeholders require information about the societal benefits of their services and attainment of organizational and societal objectives, Daraio et al. (2016) argue that effectiveness measurement cannot be constrained to supply side measures only.

3.1. Semi-nonparametric cost frontier model

We tailor the model to our empirical application, noting that the approach can be easily generalized to fit other cases. Let $x \in \Re_+$ denote the input (herein, the size of the fleet of e-scooters in use) and let $\mathbf{y} \in \Re_+^N$ denote a vector of outputs (herein, transport output (i.e., number of trips) differentiated according to time of day). In addition, there are several known covariates that influence fleet capacity utilization, including weather and day of week, which are denoted $\mathbf{z} \in \Re_+^K$.

The aim of this study is to analyze effectiveness of e-scooter providers in response to major policy changes during the Covid-19 pandemic. We apply the cost function $c(\mathbf{y})$ – minimizing capacity for given output – to model the provision of e-scooter services. The transport output varies substantially according to time-of-day, and we consequently favor a multi-output cost function where the output during the day, evening and at night are considered separate outputs. Consequently, cost minimization involves solving a peak-capacity (or pricing) problem.

Assume a panel data of I operators indexed by $i = 1,..,I$, observed over time periods $t = 1,..,T$. In this setting, the generic panel data model can be stated as

$$\ln x_{it} = \ln c(\mathbf{y}_{it}) + \boldsymbol{\delta}'\mathbf{z}_{it} + \varepsilon_{it} \tag{4}$$

where ε is a composite error term that comprises random noise, efficiency and possibly unobservable heterogeneity. The model specification in Eq. (4) is flexible and accommodates both parametric and nonparametric estimation of the cost function, c. The cost function is assumed to satisfy standard axioms in production theory.

3.2. Two-Stage estimation

Several previous studies combine productivity and efficiency analysis and the RDD framework, as identified in Section 2. As pointed out by Mergoni and De Witte (2022), most of these studies implement a conventional efficiency analysis in the *first stage* and subsequently apply the RDD approach in the *second stage*, using results from the first stage as the dependent variable.

In the present context, the two-stage estimation strategy could be outlined as follows:

Step 1: Estimate Eq. (4) using the CNLS estimator obtained by solving the following mathematical programming problem

$$\begin{aligned}
&\min \sum_{t=1}^{T}\sum_{i=1}^{N}\varepsilon_{it}^2 \\
&\text{s.t.} \\
&\ln x_{it} = \ln\phi_{it} + \boldsymbol{\delta}'\mathbf{z}_{it} + \varepsilon_{it}, \forall it \\
&\phi_{it} = \alpha_{it} + \boldsymbol{\beta}'_{it}\mathbf{y}_{it}, \forall it \\
&\phi_{it} \geq \alpha_{hs} + \boldsymbol{\beta}'_{hs}\mathbf{y}_{it}, \forall it, hs \\
&\boldsymbol{\beta}_{it} \geq \mathbf{0}, \forall it
\end{aligned} \tag{5}$$

The first equality constraint can be interpreted as a partial linear regression equation that is directly analogous to the usual linear regression equation, except for the nonparametric part governed by the second set of equations and the inequality constraints (see Johnson & Kuosmanen, 2011, 2012, for further discussion and interpretation). The first set of inequality constraints in Eq. (5) imposes convexity, while the second set of inequality constraints imposes monotonicity (Kuosmanen, 2008). The $\boldsymbol{\beta}$-coefficients can be interpreted as marginal costs, which are consequently restricted to be non-negative. The intercepts $\boldsymbol{\alpha}$ enable the estimation of the cost model under variable returns to scale, which is important in the current study to take into account that e-scooter operators differ in the size of operations. Given the optimal solution to Eq. (5), efficiency estimates Eff_{it} are computed based on the CNLS residuals (see Kuosmanen & Kortelainen, 2012, for a more detailed discussion).

Step 2: Apply the RDiT estimator in Eq. (3) using the efficiency estimates as the outcome variable, that is, $O_{it\cdot} = Eff_{it\cdot}$

While the two-stage procedure outlined above is straightforward to implement, unfortunately, it can result in misleading policy recommendations. Wang and Schmidt (2002) explain theoretically why this kind of two-step procedures are biased, and present Monte Carlo evidence showing that the bias can be severe. The most obvious problem is the endogeneity bias arising from possible correlation of the treatment with outputs $\mathbf{y}$ and/or with contextual variables $\mathbf{z}$. In the present setting, one would expect that both consumer demand and the operators' supply respond to the treatment. Indeed, this treatment effect is our main object of interest, so it would be contradictory to assume that outputs do not correlate with the treatment. However, if the outputs correlate with the treatment, but the treatment is omitted in Step 1 of the two-stage procedure, we have a classic case of *omitted variable bias*. It is equally possible that the treatment correlates with the contextual variables, either by design or just by chance, further contributing to the omitted variable bias.

A second and less widely recognized problem is that the first-step technical efficiency measures are likely to be seriously underdispersed if one applies the popular Jondrow et al. (1982) conditional efficiency estimator to obtain Eff_{it} in Step 1. Wang and Schmidt (2002) demonstrate that the results of Step 2 are then likely to be biased downward: the same shrinkage argument directly applies in the present context as well. Importantly, the downward bias of the Step 2 estimator occurs regardless of whether the treatment correlates with $\mathbf{y}$ or $\mathbf{z}$.

Finally, we note that applying the deterministic DEA estimator in the first stage does not help to avoid the endogeneity bias. In this case, the omitted variable bias works through the finite sample bias. Johnson and Kuosmanen (2012) present Monte Carlo evidence to show that the finite sample bias of DEA in the first stage carries over to the second stage estimation. In the present context, the results of Johnson and Kuosmanen (2012) suggest that the omitted variable bias becomes more severe as the correlation between the treatment and $(\mathbf{y}, \mathbf{z})$ increases. The bias can be positive or negative, which means that the treatment effects can be under- or over-estimated depending on the sign of correlation between the treatment and outputs. In the context of policy evaluation, biased estimates of the treatment effects can result in flawed policy recommendations: ineffective policy measures could be erroneously promoted as effective, and conversely, effective policy measures could be wrongly dismissed as ineffective.

3.3. One-stage estimation

To circumvent the problems described in Section 3.2, we next propose a one-stage approach that combines efficiency analysis and RDiT. This is enabled by incorporating the RDD method from Section 2.2 in the convex regression framework outlined in Section 3.1, i.e., by combining the cost function from Eq. (5) and the local linear RDiT approach from Eq. (3):

$$\begin{aligned}
&\min \sum_{i=1}^{I}\sum_{t_o-h<t<t_o}^{T}\left(\ln x_{it} - \ln\phi_{it} - \boldsymbol{\delta}'\mathbf{z}_{it} - \mu^l - \kappa^l(t-t_o)\right)^2 \\
&\min \sum_{i=1}^{I}\sum_{t_o\leq t<t_o+h}^{T}\left(\ln x_{it} - \ln\phi_{it} - \boldsymbol{\delta}'\mathbf{z}_{it} - \mu^r - \kappa^r(t-t_o)\right)^2
\end{aligned} \tag{6}$$

In contrast to the two-stage estimation strategy outlined in the previous section, the model formulation in Eq. (6) allows joint estimation of efficiency and treatment effects. Efficiency is implicitly modeled through the nonparametric frontier ϕ_{it} and the coefficients of the contextual variables, $\boldsymbol{\delta}$. The treatment effect is $\hat{\tau} = \hat{\mu}^r - \hat{\mu}^l$ as before. The joint estimation effectively avoids endogeneity biases due to possible correlation between the treatment and the outputs $\mathbf{y}$ as well as between the treatment and the contextual variables $\mathbf{z}$.

In specification (6), the estimated treatment effect $\hat{\tau} = \hat{\mu}^r - \hat{\mu}^l$ can be interpreted as a measure of *Hicks-neutral* technical change or as an *average effectiveness change* in the industry due to the treatment. In the subsequent empirical analysis, we refer to Eq. (6) as *Pooled regression*, referring to that a conventional (OLS-type) regression has been fitted to a panel dataset. To also take operator heterogeneity into account, we also include fixed effects, γ_i. Hence, this complementary specification is referred to as the *Fixed Effects* (FE) estimator:

$$\begin{aligned}
&\min \sum_{i=1}^{I}\sum_{t_o-h<t<t_o}^{T}\left(\ln x_{it} - \ln\phi_{it} - \boldsymbol{\delta}'\mathbf{z}_{it} - \gamma_i - \mu^l - \kappa^l(t-t_o)\right)^2 \\
&\min \sum_{i=1}^{I}\sum_{t_o\leq t<t_o+h}^{T}\left(\ln x_{it} - \ln\phi_{it} - \boldsymbol{\delta}'\mathbf{z}_{it} - \gamma_i - \mu^r - \kappa^r(t-t_o)\right)^2
\end{aligned} \tag{7}$$

As for the pooled regression, the estimated treatment effect is $\hat{\tau} = \hat{\mu}^r - \hat{\mu}^l$ for the FE estimator.

Eqs. (6 and 7) implicitly assume that the non-parametric function ϕ is time-invariant, i.e., the cost function is the same before and after the treatment. Subsequently, we refer to the time-invariant cost function as the *global frontier*. Further flexibility can be added by allowing the frontier function to (potentially) change with the treatment. This approach, which is formalized by Eq. (8), is subsequently referred to as the *temporal* frontier approach.

$$\begin{aligned}
&\min \sum_{i=1}^{I}\sum_{t_o-h<t<t_o}^{T}\left(\ln x_{it} - \ln\phi^l_{it} - \boldsymbol{\delta}'\mathbf{z}_{it} - \gamma_i - \mu^l - \kappa^l(t-t_o)\right)^2 \\
&\min \sum_{i=1}^{I}\sum_{t_o\leq t<t_o+h}^{T}\left(\ln x_{it} - \ln\phi^r_{it} - \boldsymbol{\delta}'\mathbf{z}_{it} - \gamma_i - \mu^r - \kappa^r(t-t_o)\right)^2
\end{aligned} \tag{8}$$

Using Eq. (8), expected outcomes at t_0 are:

$$\begin{aligned}
&\ln\hat{\phi}^l_{it_0} + \hat{\boldsymbol{\delta}}'\mathbf{z}_{it_o} + \hat{\gamma}_i + \hat{\mu}^l + \hat{\kappa}^l(t_o - t_o) \\
&\ln\hat{\phi}^r_{it_0} + \hat{\boldsymbol{\delta}}'\mathbf{z}_{it_o} + \hat{\gamma}_i + \hat{\mu}^r + \hat{\kappa}^r(t_o - t_o)
\end{aligned} \tag{9}$$

and the estimated treatment effect consequently comprises frontier and industry-average effectiveness changes:

$$\begin{aligned}
\hat{\tau} &= \left(\ln\hat{\phi}^r_{it_0} + \hat{\mu}^r\right) - \left(\ln\hat{\phi}^l_{it_0} + \hat{\mu}^l\right) \\
&= \underbrace{\left(\ln\hat{\phi}^r_{it_0} - \ln\hat{\phi}^l_{it_0}\right)}_{\text{Frontier change}} + \underbrace{\left(\hat{\mu}^r - \hat{\mu}^l\right)}_{\text{Industry effectiveness change}}
\end{aligned} \tag{10}$$

Finally, we relax the stringent assumption that effectiveness changes uniformly across operators and allow operator-specific treatment effects. Following the state-of-the art contribution by Calonico et al. (2025), we introduce heterogenous treatment effects by accommodating local regression with pretreatment covariate interaction. As our dataset follows the same decision-making units over time, it is natural to consider interactions with operator-specific dummy variables, i.e., to accommodate *firm-specific* treatment effects. Heterogenous treatment effects are accommodated by Eq. (11), where treatment and running variable parameters now are considered firm-specific. This implies that treatment effects could – in principle – be estimated separately for each firm using standard RD methods for average treatment effect estimation. However, since the current modeling involves the estimation of frontiers and impacts of contextual variables that are not specific to each decision-making unit, it is imperative to estimate the firm-specific treatment effects jointly using a system of equations approach.

$$\begin{aligned}&\min\sum_{i=1}^{I}\sum_{t_o-h<t<t_o}^{T}\left(\ln x_{it}-\ln\phi_{it}^{l}-\boldsymbol{\delta}'\mathbf{z}_{it}-\mu_i^l-\kappa_i^l(t-t_o)\right)^2\\&\min\sum_{i=1}^{I}\sum_{t_o\le t<t_o+h}^{T}\left(\ln x_{it}-\ln\phi_{it}^{r}-\boldsymbol{\delta}'\mathbf{z}_{it}-\mu_i^r-\kappa_i^r(t-t_o)\right)^2\end{aligned} \tag{11}$$

The heterogenous treatment effects approach enables decomposing the estimated and overall treatment effect into *operator-specific* frontier and effectiveness changes:

$$\begin{aligned}\widehat{\tau}&=\left(\ln\widehat{\phi}_{it_0}^{r}+\widehat{\mu}_i^r\right)-\left(\ln\widehat{\phi}_{it_0}^{l}+\widehat{\mu}_i^l\right)\\&=\underbrace{\left(\ln\widehat{\phi}_{it_0}^{r}-\ln\widehat{\phi}_{it_0}^{l}\right)}_{\text{Frontier change}}+\underbrace{\left(\widehat{\mu}_i^r-\widehat{\mu}_i^l\right)}_{\text{Effectiveness change}}\end{aligned} \tag{12}$$

3.4. Computation

In this section, we discuss computation of the one-stage RDiT-CNLS estimator as a mathematical programming formulation. For brevity, we only present the CNLS formulation of Eq. (11).

For notational convenience, we start by defining subsets of T. Let

$$\begin{aligned}T^l&=\{t:t_0-h<t<t_0\}\\T^r&=\{t:t_o\le t<t_o+h\}\end{aligned} \tag{13}$$

Using this notation, the empirical counterpart to Eq. (11) is defined as:

$$\begin{aligned}&\min\left(\sum_{t=1}^{T^l}\sum_{i=1}^{N}\varepsilon_{it}^2+\sum_{t=T^l+1}^{T^r}\sum_{i=1}^{N}\varepsilon_{it}^2\right)\\&\text{s.t.}\\&\ln x_{it}=\ln\left(\alpha_{it}^l+\boldsymbol{\beta}_{it}^{l\,\prime}\mathbf{y}_{it}\right)+\mu_i^l-\kappa_i^l(t-t_o)+\boldsymbol{\delta}'\mathbf{z}_{it}+\varepsilon_{it},\forall it\in T^l\\&\ln x_{it}=\ln\left(\alpha_{it}^r+\boldsymbol{\beta}_{it}^{r\,\prime}\mathbf{y}_{it}\right)+\mu_i^r-\kappa_i^r(t-t_o)+\boldsymbol{\delta}'\mathbf{z}_{it}+\varepsilon_{it},\forall it\in T^r\\&\alpha_{it}^l+\boldsymbol{\beta}_{it}^{l\,\prime}\mathbf{y}_{it}\ge\alpha_{hs}^l+\boldsymbol{\beta}_{hs}^{l\,\prime}\mathbf{y}_{it},\forall it\in T^l,hs\in T^l\\&\alpha_{it}^r+\boldsymbol{\beta}_{it}^{r\,\prime}\mathbf{y}_{it}\ge\alpha_{hs}^r+\boldsymbol{\beta}_{hs}^{r\,\prime}\mathbf{y}_{it},\forall it\in T^r,hs\in T^r\\&\boldsymbol{\beta}_{it}\ge0,\forall it\end{aligned} \tag{14}$$

Note that in contrast to the two-stage approaches used in the previous literature, Eq. (14) simultaneously estimates the frontier and the treatment effect. We estimate Eq. (14) in GAMS for the subsequent empirical assessment.

3.5. Optimal bandwidth and robust standard errors

For statistical inferences, it is important to note that while the frontier estimator in Eq. (14) has a nonparametric rate of convergence, the parametric part behaves very similar to the usual linear regression: Johnson and Kuosmanen (2011, Theorem 2) show that the parameter estimators of the parametric part are asymptotically normally distributed. Therefore, the standard tools to find the optimal bandwidth and the robust standard errors can be applied for the proposed RDiT-CNLS estimator. This is a major advantage of the one-stage estimation approach over the previous two-stage approaches discussed in Section 3.2.

The bandwidth parameter controls what is considered “close” in time to the reopening and is therefore a crucial parameter for the assessment. The choice of optimal bandwidth for the RDD estimator has received ample attention in the literature. Bandwidth selection focuses on the trade-off among bias (or misspecification) and variance of the RDD point estimator, where a narrow bandwidth tends to reduce the bias but increases variance. Imbens and Kalyanaraman (2012) propose a mean squared error (MSE) criterion for the RDD estimator; cf. Eq. (15). The optimal bandwidth minimizes the MSE criterion.

$$MSE(h)=E\left[(\widehat{\tau}-\tau)^2\right]=E\left[\left((\widehat{\mu}^r-\mu^r)-(\widehat{\mu}^l-\mu^l)\right)^2\right] \tag{15}$$

In constructing asymptotically valid confidence intervals, the bias of the RD estimator must be considered. Calonico et al. (2014) propose bias-corrected confidence intervals:

$$CI=\left[\{\widehat{\tau}(h)-\widehat{b}\}\pm\Phi\sqrt{\widehat{v}}\right] \tag{16}$$

where b denotes the bias-correction and v denotes the variance estimator.

For the empirical assessment, we exploit the software package *rdrobust* (Calonico et al. 2017), implemented in Stata, to compute optimal bandwidth and robust standard errors. We rely predominantly on default settings, including the use of MSE-optimal bandwidth selection. For evaluation of optimal bandwidth and robust standard errors subject to heterogenous treatment effects, we rely on the state-of-the-art package *rdhte/rdbwhte*, which became available in R in 2025. This package implements the MSE-optimal bandwidth selection developed by Calonico et al. (2025).

To harmonize the CNLS estimation (Eq. (14)) with the selection of optimal bandwidth and robust standard errors (Eqs. (15) and 16), we apply the algorithm presented by Fig. 1. Example codes for the computation of the RDiT-CNLS estimator are available as supplementary material.

4. Application to e-scooters

The electric scooter or e-scooter for short is a relatively new invention, at least when considering commercialization. During the last three years, e-scooters have received increasing attention, both within research and in the society in general. Although a considerable number of studies have been published within the last couple of years, we are not aware of other studies involving measurement of efficiency or effectiveness. However, there is substantial research on efficiency analysis in other parts of the transport sector. In an early meta-study, Brons et al. (2005) find no significant differences in technical efficiency rates between parametric and non-parametric frontier efficiency studies. In their review of public transport economics, Hörcher and Tirachini (2021) report that purely technically oriented efficiency analyses typically are based on intermediate outputs, such as number of vehicles, vehicle-kilometres, or seat-kilometres. We refer to Victorino and Peña (2023) for a more targeted review of frontier efficiency analyses within the transport sector (cf. Jarboui, Forget & Boujelbene 2012 for an earlier review). A noteworthy contribution is the paper by Caggiani et al. (2021) which, like the current paper, focuses on micromobility. Contrary to our contribution, Caggiani et al. (2021) evaluate shared bicycles in an urban setting using the deterministic DEA method.

While the literature on efficiency analysis with applications in the transport sector is relatively well developed, fewer studies assess effectiveness. In an early contribution, Karlaftis (2004) applies DEA to

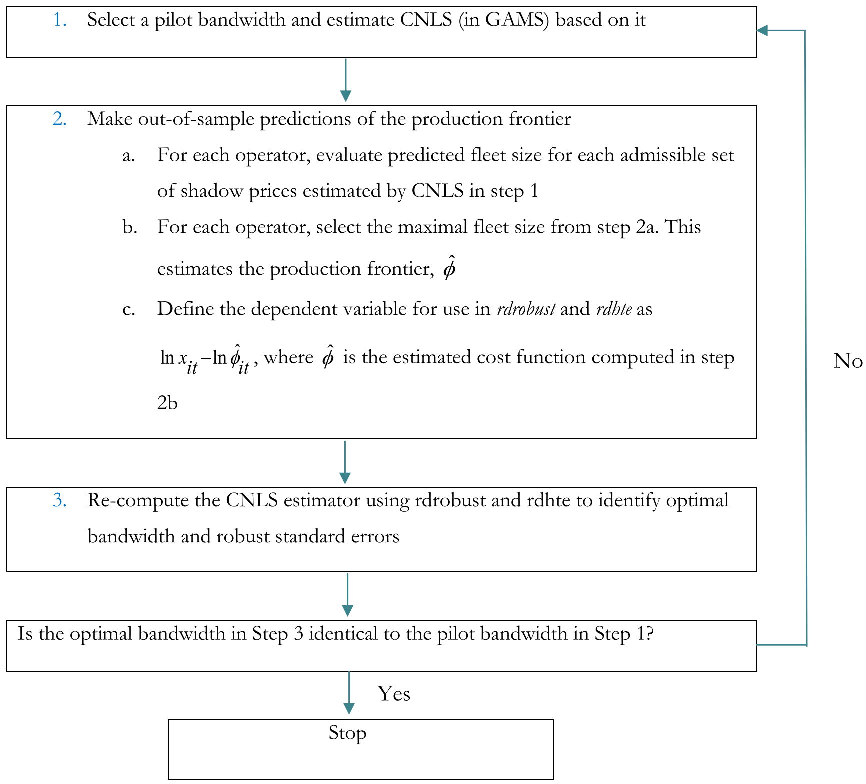

Fig. 1. Flowchart of the estimation approach.

examine the relationship between efficiency, effectiveness, and economies of scale in urban transit systems. Diana and Daraio (2014) point out that studies of transport effectiveness may play a role in transport planning and policy design, but they call for further research on the topic. This paper contributes to that end, being the first to shed light on the effectiveness of e-scooter providers.

Several studies on e-scooter services including Wang et al. (2022) and Fearnley (2022) focus on the substitutability among e-scooters and other modes. Using a web survey directed towards public transport users in Oslo, Fearnley, Johnson and Berge (2020) find that shared e-scooters is a popular first or last mile mode for many passengers, with potential for higher use in case of tighter integration between modes.

The absence of a well-organized e-scooter system capable of meeting the existing demand for scheduled trips will likely undermine users' confidence in arriving at their destinations on time, causing them to switch to other modes of transport. Infrastructure for shared e-scooters may also be a tool for absorbing demand without substantially interfering with the current traffic system. We refer to Mitropoulos et al. (2023) for a review of the literature.

How contextual variables impact e-scooter demand is an important research topic. For example, Hardt and Bogenberger (2018) identify subjective safety, weather conditions and baggage capacity as restricting attributes for e-scooter mobility. The study by Tuli et al. (2021) shows that e-scooter demand fluctuates subject to weather conditions and external factors such as gasoline prices. This stream of research has been instrumental in identifying suitable contextual variables for our study.

Damage costs arise from the use of shared e-scooters: Hollingsworth et al.'s (2019) investigate associated life-cycle pollution and Kobayashi's (2019) investigate e-scooter related trauma. The latter identifies use of alcohol and illicit substances, and very limited use of helmets as important contributing factors.

E-scooters have not only become popular among users as efficient and enjoyable mode of transport, but also unpopular among other parts of the population, inter alia due conflicts regarding space, speed, safety and immature regulations; See Gössling (2020) for a mapping of concerns related to e-scooter usage pre and post their introduction. Thus, how to regulate the operation and use has become a topic both in public debate and research. Button et al. (2020) provide an overview of challenges related to e-scooters and the regulative response in the United States prior to the corona pandemic. Aarhaug et al. (2023) study introduction of a low-cost carrier in the e-scooter market in Drammen and the introduction of a fleet cap for operators in Oslo. They find evidence of considerable scale advantages and relatively high price sensitivity for joy rides compared to trips made for traveling purposes. Aarhaug, Fearnley and Johnson (2023) find that e-scooters are both substitutes and complements public transport in Oslo. Other relevant investigations and discussions on regulations of shared e-scooters include Fearnley (2020) and Gössling (2020). The current paper provides important empirical evidence on the impact of public policy on e-scooter fleet capacity utilization, and thus indirectly on the external costs of e-scooter services.

4.1. The case areas

Oslo is the capital city of Norway, located in southeastern Norway at the innermost part of the Oslofjord. According to Statistics Norway, the population was 1,036,059 in the urban area and 693,494 in the municipality in 2020. Drammen is located 44 km southwest of Oslo, at the Drammens fjord. The city had a population of 109,416 in the urban area and 101,386 in the municipality in 2020. Both cities' urban public transportation systems encompass buses, shared bikes, shared e-scooters, taxis, and trains, while the Oslo system also involves ferries, metro, and trams. They feature a somewhat hilly terrain, with elevations ranging from sea level to several hundred meters, and city centers situated at lower elevations.

During our study period, six operators of shared e-scooters were active in Oslo, while two were active in Drammen. A rental fee typically involved a staring fee of 1 to 1.5 euro per trip followed by a per minute usage price of 1.0 to 1.5 euro. We refer to Aarhaug et al. (2023) and Aarhaug, Fearnley and Johnson (2023) for further details.

4.2. The dataset

In the empirical part of our study, we utilize data obtained from e-scooter operators in Oslo and Drammen. The dataset contains daily information about the e-scooter market between January 1st of 2019 to August 31st of 2021. The fleet size available to users on a daily basis is regarded as the sole input to the effectiveness analysis. We consider time-of-day demand as outputs, classifying the day into *nighttime* (operationally defined as 23 PM to 7 AM), *daytime* (operationally defined as 7 AM to 15 PM) and *evening* (operationally defined 15 PM to 23 PM). This enables considering optimal fleet size subject to peak and off-peak demand, which is a key characteristic of the transport sector. For the e-scooter market, the number of trips typically boom in the afternoon, while reaching its minimum in the evening and at night.

As contextual variable, we exploit data concerning weather conditions from the Norwegian Meteorological Institute, more specifically concerning precipitation and temperature. In addition, we apply a dummy which indicates whether any day under consideration is a business day or not. Summary statistics of the dataset are presented by Table 1, which classifies variables into outputs, inputs and contextual variables.

Note that due to a non-disclosure agreement with the operators, we are unable to identify them by name in the subsequent analysis. We instead consistently refer to them as Operators A-H throughout.

4.3. Trends in E-Scooter usage

Many important characteristics of the e-scooter markets of Oslo and Drammen become apparent by visual inspection. The main patterns are depicted in Fig. 2, which shows the development of the number of trips from January 2019 to August 2021. First, it reveals strong seasonality in the use of e-scooters, with high use during the summer months and low use during the winter months. Note that the winter in the Greater Oslo Region often is characterized by snow and ice, such that roads and sidewalks will be less suited for e-scooters. Most operators withdraw their services during the winter season. Second, the use of e-scooters increases considerably over time, adjusted for seasonality. Note that we do not have data for Drammen prior to April 2020. Yet, the number of trips before this point was relatively low.

Third, the boom periods for use of e-scooters starts at different points in time each year. This could be explained by variations in e.g., weather conditions, but in our case, differences are influenced by the Covid-19 pandemic through lockdown and variation in infection rates.

Fig. 3 shows the development in number of daily trips *by e-scooter operator* from January 2020 to August 2021, while Fig. 4 shows the corresponding development in fleet *size* per operator. Both figures highlight the two key dates for reopening after lockdown on 27th of April 2020 and 26th of May 2021, which are indicated using vertical lines.

The two dates marked the end of long periods of social isolation, and the restrictions lifted include closing of bars, restaurants, gyms, cinemas, theaters and concert halls, as well as prohibition of social gathering. Reopening was announced short time before its implementation, thus giving the e-scooter providers limited time to adjust their supply ahead of the opening dates. For example, the lift of sanctions on Wednesday 26th of May 2021 was announced on Friday afternoon the preceding week.

Figs. 3 and 4 reveal that changes in Covid-policies have repercussions for the e-scooter market. While it is clear from these figures that the reopening dates affected firms asymmetrically, there is a tendency that the number of trips increase substantially after the treatment. Several of the operators appear to adjust their fleet to meet the increase in demand shortly after the treatment date.

A preliminary investigation into the consequences of treatment on effectiveness is undertaken by looking at the average number of trips per e-scooter per day 30 days before and after the reopening dates, which are presented by Table 2. Among the eight e-scooter operators under consideration, only three were active during the first reopening, while six were active during the last reopening.

5. RDiT results

We start by looking at how reopening of Norway has impacted number of trips and fleet size, before we turn to how effectiveness is impacted.

5.1. Trips and fleet sizes

Table 3 presents the results of RDiT-analyses of the impact of reopening dates on industry-average input (i.e., fleet size) and output (i.e., number of trips) using both pooled regression and FE specifications. The parameter estimates report the absolute (average) change in input and output after treatment. Throughout, we report the estimated treatment effect (RD Estimate), conventional p-values (Conv. p.val), robust p-values (Rob. p.val) and bandwidths (BW model) applied in the estimation of the model and the bias correction. We use the *rdrobust* package with the default MSE-optimal bandwidth criteria for the assessment. We refer to Section 3.5 for additional details about the RD approach and the computation of optimal bandwidths and robust standard errors.

Considering the pooled regression specification in Table 3, the treatments appear not to have had statistically significant impacts on inputs and outputs at the industry level (i.e., when considering the average treatment effect only). However, this can be attributed to the heterogenous e-scooter market, which becomes clear when turning to the results of the FE estimator (that considers operator-specific heterogeneity) as changes in trips at the industry level are statistically significant at the 10 percent level, and at the 1 percent level in the latter treatment period. Change in industry input is also statistically significant at the 10 percent level for the latter treatment date.

For brevity, and based on our initial screening, we subsequently focus on the latter reopening date in 2021. The initial results previously presented indicate statistically significant changes at both input and output level, and the market was denser in 2021 compared to 2020.

Table 1
Summary statistics of the dataset used for empirical analysis.

Category	Variables	N	Mean	Sd. Dev	Min	Max
Output	Trips, total (no)	6,488	3,082.43	6,464.08	0.00	56,003.00
	Trips, daytime (no)	6,488	895.20	1,795.50	0.00	15,671.00
	Trips, evening (no)	6,488	1,807.94	3,945.02	0.00	35,342.00
	Trips, night (no)	6,488	379.29	892.80	0.00	10,063.00
Input	Fleet (no)	4,999	889.71	1,213.77	0.00	7,661.00
Contextual variables	Precipitation (mm)	6,488	2.97	6.92	0.00	58.60
	Temperature (°C)	6,488	9.55	7.47	−11.35	25.13
	Week day[a] (dummy)	6,488	1.30	0.46	1.00	2.00
	City[b] (dummy)	6,488	1.14	0.34	1.00	2.00

[a] 1 if business day, 2 if Weekend.
[b] 1 if Oslo, 2 if Drammen.

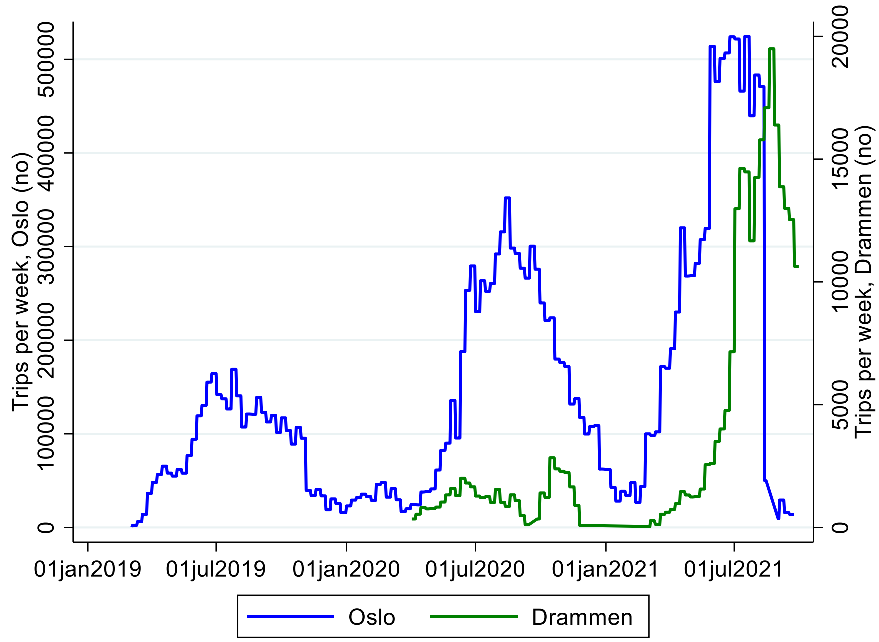

Fig. 2. Total number of e-scooter trips in Oslo and Drammen per week from January 2019 to August 2021.

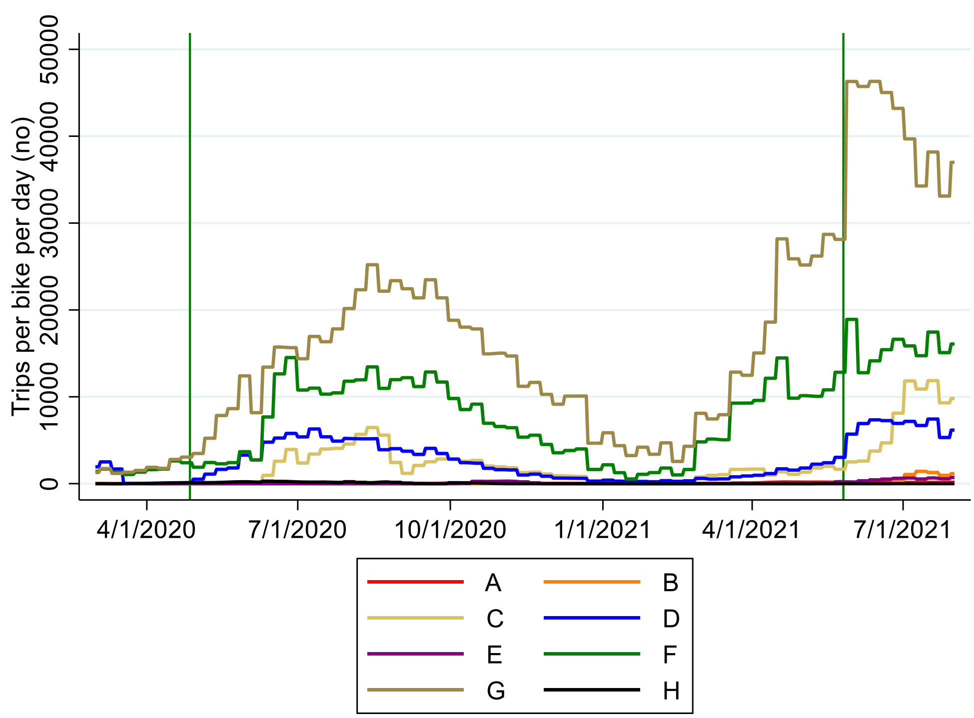

Fig. 3. Number of trips per day per operator. Reopening dates indicated by vertical lines.

During the second reopening, five of the operators covered by the dataset were active in Oslo, while one operator was active in Drammen. According to Table 4, the number of trips increased significantly after treatment for four of the active firms. Regarding fleet size, positive and significant results at a ten percent significance level are found for Operators A, F, and G, where the first-mentioned firm is a challenger and the two later-mentioned were market leaders at the time. The RD estimates for Operator E turn out to be negative and significant.

5.2. *Effectiveness*

We now turn the RDiT-CNLS results, considering the impacts of the second reopening on e-scooter operators' effectiveness. We refer to Sections 3.3 and 3.4 for details on model specifications and computation. Section 3.5 describes the identification of optimal bandwidths and robust standard errors.

We first consider the results for the average treatment effect estimators presented by Eqs. (6)-(8). Overall, the results suggest that the Covid policy change did not impact the e-scooter operators' performance, confer Table 5.

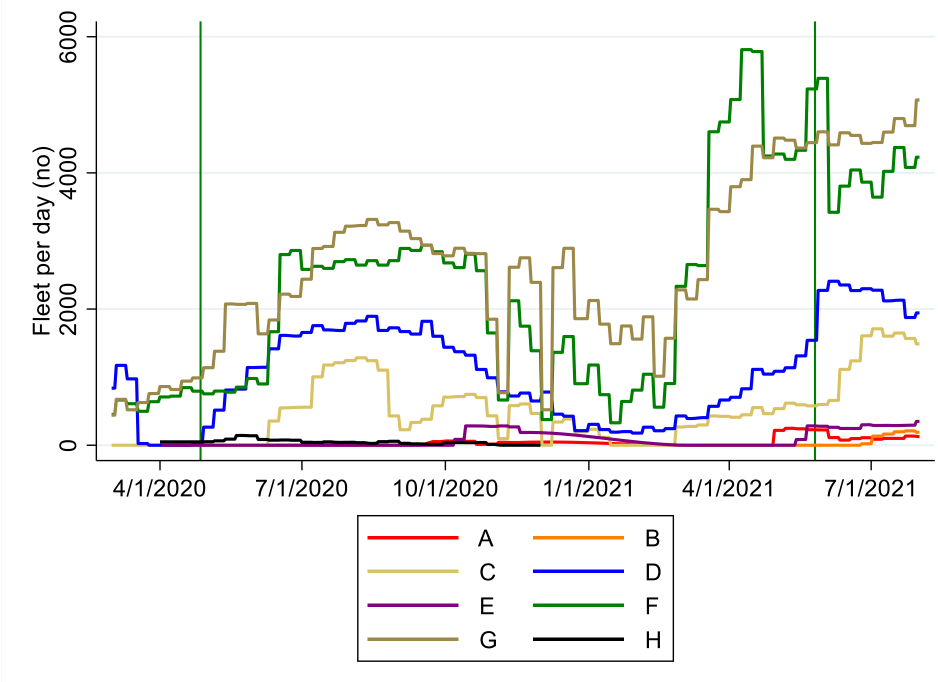

Fig. 4. Fleet size per day per operator. Reopening dates indicated by vertical lines.

Table 2
Average number of trips per e-scooter per day. 30 days before and after treatments.

	Before: 27. April 2020	After: 27. April 2020	Before: 26. May 2021	After: 26. May 2021
Operator A			0.68	1.44
Operator B				
Operator C			2.79	3.74
Operator D			1.79	2.84
Operator E			0.73	1.42
Operator F	2.61	2.77	2.36	3.61
Operator G	2.51	3.62	5.99	9.86
Operator H	1.86	1.77		

Table 3
Pooled and Fixed Effects RDiT-analysis of trips and fleet sizes. Point estimates, p-values and optimal bandwidths.

	Trips		Fleet	
	27. April 0.2020	26. May 2021	27. April 0.2020	26. May 2021
Pooled regression				
RD Estimate	−145.70	3,089.20	98.34	185.20
Conv. p-val.	0.56	0.20	0.20	0.69
Rob. p-val.	0.40	0.30	0.20	0.75
BW model (h)	40.25	27.88	45.33	25.94
BW bias (b)	85.36	46.48	86.11	44.97
Eff no of obs	618	440	577	371
Fixed Effects*				
RD Estimate	−214.60	2,941.60	−34.58	123.40
Conv. p-val.	0.12	0.00	0.23	0.16
Rob. p-val.	0.06	0.00	0.53	0.08
BW model (h)	41.70	33.06	33.00	33.06
BW bias (b)	80.42	50.65	33.00	33.06
Eff.no of obs	692	536	520	536

* Fixed Effects implemented using the least squares dummy variable estimator.

As indicated by the analyses in Section 5.1, the e-scooter market is heterogenous. We are therefore concerned that the average treatment results in Table 5 might blur the actual outcome of the policy reform, which can best be evaluated at the individual level. Consequently, Table 6 presents the empirical counterparts to Eq. (11), considering both global and temporal frontiers.

As explained in Section 3.5, we utilize the state-of-the-art package *rdhte/rdbwhte* to estimate heterogenous treatment effects subject to optimal bandwidths that are selected based on the MSE-criterion. In our setting, the *rdhte* package presents *relative* treatment effects (i.e., it presents the treatment effect of the first decision making unit in the dataset, and subsequently the difference between the effects of other units relative to the treatment effect of the initial unit). To present parameter estimates and robust standard errors for *absolute* treatment effects for all e-scooter operators in the sample, Table 6 also presents operator-specific treatment effects based on the *rdrobust* package subject to the preprocessed estimates of the production frontier and the effects of contextual variables from GAMS. The computations of operator-specific treatment effects are implemented subject to the MSE-optimal bandwith identified by the *rdbwhte* package, both for the cost models with global and temporal frontiers.

Using the modeling approach outlined in Section 3.5, we find MSE-optimal bandwidths of 24 days for the model with global frontier and 30 days for the model with temporal frontier. The results suggest that treatment effects are heterogenous across operators, where some (e.g., units C, F and G subject to a global frontier) experience higher effectiveness levels after treatment, while other operators exhibit a deterioration in performance. The classification of "winners" and "losers" in terms of effectiveness change is robust across the global and temporal frontier model specifications. However, taking robust standard errors into account, we find mixed and weak evidence overall that the

Table 4
Firm-specific RDiT-analysis of trips and fleet size. Point estimates, p-values and optimal bandwidths per firm for T=May 26, 2021.

	Oper. A	Oper. C	Oper. D	Oper. E	Oper. F	Oper. G
Trips						
RD estimate	80.08	550.11	1,897.02	−70.31	6,797.16	13,968.04
Conv. p-val.	0.04	0.38	0.02	0.21	0.04	0.02
Rob. p-val.	0.04	0.22	0.09	0.11	0.04	0.07
BW model (h)	16.60	10.57	20.77	22.00	17.27	15.71
BW bias (b)	37.50	22.34	45.17	39.64	35.15	29.43
Fleet						
RD estimate	75.12	69.58	372.85	−106.54	1574.91	261.71
Conv. p-val.	0.03	0.45	0.15	0.00	0.02	0.10
Rob. p-val.	0.02	0.33	0.27	0.00	0.02	0.10
BW model (h)	8.96	8.80	17.52	10.90	13.39	19.79
BW bias (b)	22.92	19.06	37.61	28.23	30.29	37.50

Table 5
Pooled regression and Fixed Effects RDiT-analysis of transport effectiveness subject to global and temporal frontiers. Covariate-adjusted estimates. Point estimates, p-values and bandwidths.

	Global frontier 26. May 2021	Temporal frontier 26. May 2021
Pooled regression		
RD Estimate	−0.01	1.15
Conv. p-val.	0.89	0.00
Rob. p-val.	0.88	0.00
BW model (h)	28.25	27.68
BW bias (b)	47.58	49.36
Fixed Effects*		
RD_Estimate	0.03	−0.02
Conv. p-val.	0.51	0.56
Rob. p-val.	0.68	0.23
BW model (h)	28.71	28.33#
BW bias (b)	49.32	47.61#

* Fixed Effects implemented using the least squares dummy variable estimator.
# [2]Initial bandwidth for CNLS estimation: h= 27.

Table 6
RDiT-analysis of transport effectiveness subject to heterogenous treatment effects. Treatment period: 26. May 2021. Covariate-adjusted estimates. Point estimates and robust p-values.

Frontier	Global		Temporal	
Treatement effect	Absolute	Relative	Absolute	Relative
BW model (h)	$h = 24$	$h = 24$	$h = 30$	$h = 30$
Oper. A	0.204***	0.204	−0.119	−0.119
	(0.002)	(0.137)	(0.780)	(0.859)
Oper. C	−0.038*	−0.241*	−0.023**	0.096
	(0.085)	(0.087)	(0.028)	(0.366)
Oper. D	0.096	−0.108	0.016	0.135
	(0.102)	(0.278)	(0.753)	(0.780)
Oper. E	0.391	0.187	0.520	0.639
	(0.964)	(0.244)	(0.832)	(0.985)
Oper. F	−0.100	−0.303*	−0.120	−0.001
	(0.197)	(0.076)	(0.126)	(0.478)
Oper. G	−0.095	−0.299*	−0.148	−0.029
	(0.317)	(0.086)	(0.360)	(0.650)

reopening has affected the effectiveness of e-scooter operators in Norway. The most robust effect is for operator C, for which the absolute effectiveness change is deemed statistically significant at the 10-percent level both for the global and temporal model specifications.

While the *rdhte* package can be seen as offering an approach to robustness testing of pairwise statistical differences between operator-specific treatment effects for our application, we also implement a Wald test for the null hypothesis that absolute treatment effects are uniform across e-scooter operators (i.e., that a model containing solely the average treatment effect gives a better fit to the data). The null hypothesis is rejected at the 1-percent level, which suggests that the accommodation of heterogenous treatment effects is valuable for empirical analysis of interventions in a market comprising diverse suppliers.

This Section has provided comprehensive empirical evaluation on the impact of the reopening on the demand for e-scooter services and the corresponding supply and effectiveness of the operators. The result points towards a growing market after the reopening and that the impact of operators differs. We end the result section on the note that our findings suggest that the e-scooter industry has in general not been able to absorb the positive demand shock that followed from lifting of sanctions due to the Covid-19 pandemic. Empirical evidence of low capacity utilization (cf., Table 2) and performance and limited absorptive capacity (cf., Table 6) is likely to characterize an industry in its infantility, with a vast potential to improve performance and its competitiveness in the transport market in the coming years.

6. Conclusions

While causal inference is essential in many other disciplines, it has picked up interest in the efficiency analysis community only recently. Although there exist attempts to combine quasi-experimental RDD with efficiency analysis, most previous studies use a two-stage approach that does not appropriately address the correlation between efficiency and treatment. As a result, the two-stage approach can yield biased estimates of the treatment effect and result as misguided policy recommendations. To mitigate this problem, we propose a one-stage method that combines non-parametric frontier estimation with the RDD, which enables distinguishing the contribution of treatment to efficiency and technical changes, respectively.

Thus far, heterogenous treatment effects have received limited attention in the RDD literature, where the *average* treatment effect is of primary interest. To allow for heterogenous treatment effects, we introduce a novel system of equations where the treatment effects are *firm-specific*, while the cost frontier and contextual variables are common to all firms. Our empirical results indicate that estimated treatment effects can indeed differ considerably across firms. In general, since the average treatment effect might mask heterogenous responses to a treatment, it is possible that the average treatment effect is statistically insignificant while the treatment is effective for some subsets of treated units. This issue clearly warrants more attention in future research. A better understanding of why treatment may only affect some firms but not others can help policy makers to develop more tailored policies and to better understand distributional aspects of policy interventions.

As part of the methodological development, we showcase that treatment effects may be decomposed into frontier and efficiency (effectiveness) changes. For the empirical analysis, we focus solely on the latter, being the key metric of interest to this study. This is partly because the investigation warrants statistical inference, and that appropriate tools for estimation of robust standard errors for frontier shifts in CNLS are not available. We regard the development of methods for estimation and inference of both frontier and efficiency change estimates from convex regression as a fruitful area for future research.

This study has analyzed effectiveness of e-scooter providers' responses to major policy changes during the Covid-19 pandemic to shed light on their capabilities to respond to demand shocks. It is the first to address operational effectiveness (i.e., the relationship among inputs and transport demand) in the market for e-scooters.

While the overall result is that the e-scooter operators have only to a limited degree been able to exploit market potentials from a rapid increase in demand after the lifting of restrictions due to the Covid-19 pandemic, our results consistently show that limiting the scope of the analysis to (industry) average treatment effects is insufficient to understand treatment effects in heterogenous and volatile markets.

The empirical findings of low capacity utilization and performance of e-scooter operators are likely to characterize a young market with substantial potential to further improve efficiency and effectiveness of operations. By exploiting this potential, the competitiveness of e-scooters can substantially improve short-distance travel in the urban context. Low effectiveness is also likely to have repercussions for other transport users, such as negative impacts on pedestrians from prolonged improper parking of e-scooters.

The Norwegian e-scooter market remained largely unregulated during its first years. Our results suggest that policy measures should be directed towards inefficiencies in current practices. With seemingly vast over-capacity of the e-scooter fleet, maximal capacity constraints can be an effective measure to promote operator performance. Combined with efficient capacity regulation (e.g., through auctions or tradeable quota schemes), fleet size constraints can be welfare-enhancing for operators, users and third parties alike.

CRediT authorship contribution statement

Kenneth Løvold Rødseth: Writing – original draft, Visualization, Software, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Timo Kuosmanen:** Writing – original draft, Validation, Methodology, Investigation, Conceptualization. **Rasmus Bøgh Holmen:** Writing – original draft, Visualization, Validation, Formal analysis.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.ejor.2025.11.011.

References

Aarhaug, J., Fearnley, N., Hartveit, K. J. L., & Johnsson, E. (2023). Price and competition in emerging shared e-scooter markets. *Research in Transportation Economics, 98*, Article 101273.

Agasisti, T., & Soncin, M. (2021). Higher education in troubled times: On the impact of Covid-19 in Italy. *Studies in Higher Education, 46*(1), 86–95.

Badunenko, O., D'Inverno, G., & De Witte, K. (2023). On distinguishing the direct causal effect of an intervention from its efficiency-enhancing effects. *European Journal of Operational Research, 310*, 432–447.

Bakolis, I., Stewart, R., Baldwin, D., Beenstock, J., Bibby, P., Broadbent, M., Cardinal, R., Che, S., Chinnasamy, K., Cipriani, A., Douglas, S., Horner, P., Jackson, C. A., John, A., Joyce, D. W., Lee, S. C., Lewis, J., McIntosh, A., Nixon, N., Osborn, D., Phiri, P., Rathod, S., Smith, T., Sokal, R., Waller, R., & Landau, S. (2021). Changes in daily mental health service use and mortality at the commencement and lifting of COVID-19 'lockdown' policy in 10 UK sites: A regression discontinuity in time design. *BMJ open, 11*(5), Article e049721.

Banker, R. D., & Natarajan, R. (2008). Evaluating contextual variables affecting productivity using data envelopment analysis. *Operations Research, 56*, 48–58.

Becker, S. O., Egger, P. H., & Von Ehrlich, M. (2013). Absorptive capacity and the growth and investment effects of regional transfers: A regression discontinuity design with heterogeneous treatment effects. *American Economic Journal: Economic Policy, 5*(4), 29–77.

Brons, M., Nijkamp, P., Pels, E., & Rietveld, P. (2005). Efficiency of urban public transit: A meta analysis. *Transportation,, 32*, 1–21.

Button, K., Frye, H., & Reaves, D. (2020). Economic regulation and E-scooter networks in the USA. *Research in Transportation Economics, 84*, Article 100973.

Caggiani, L., Camporeale, R., Hamidi, Z., & Zhao, C. (2021). Evaluating the efficiency of bike-sharing stations with data envelopment analysis. *Sustainability, 13*(2), 881.

Calonico, S., Cattaneo, M. D., Farrell, M. H., & Titiunik, R. (2017). rdrobust: Software for regression-discontinuity designs. *The Stata Journal, 17*(2), 372–404.

Calonico, S., Cattaneo, M.D., Farrell, M.H., Palomba, F., & Titiunik, R. (2025). Treatment effect heterogeneity for regression discontinuity designs. Working paper. URL: https://rdpackages.github.io/references/Calonico-Cattaneo-Farrell-Palomba-Titiunik_2025_HTERD.pdf.

Calonico, S., Cattaneo, M. D., & Titiunik, R. (2014). Robust nonparametric confidence intervals for regression-discontinuity designs. *Econometrica : Journal of the Econometric Society, 82*(6), 2295–2326.

Chambers, R. G., & Serra, T. (2019). Estimating ex ante cost functions for stochastic technologies. *Americal Journal of Agricultural Economics, 101*, 807–824.

Daraio, C., Diana, M., Costa, F. D., Leporelli, C., Matteucci, G., & Nastasi, A. (2016). Efficiency and effectiveness in the urban public transport sector: A critical review with directions for future research. *European Journal of Operational Research, 248*, 1–20.

Daraio, C., Simar, L., & Wilson, P. W. (2018). Central limit theorems for conditional efficiency measures and tests of the 'separability'condition in non-parametric, two-stage models of production. *The Econometrics Journal, 21*(2), 170–191.

Dementiev, A., & Han, H. J. (2020). A theory of deregulation in public transport. *Research in Transportation Economics, 83*, Article 100953.

Diana, M., & Daraio, C. (2014). Evaluating the effectiveness of public transport operations: A critical review and some policy indicators. *International journal of transport economics: Rivista internazionale di economia dei trasporti: XLI, 1*(2014), 75–108.

D'Inverno, G., Smet, M., & De Witte, K. (2021). Impact evaluation in a multi-input multi-output setting: Evidence on the effect of additional resources for schools. *European Journal of Operational Research, 290*, 1111–1124.

Fan, J., & Gijbels, I. (1996). *Local polynomial modelling and its applications: Monographs on statistics and applied probability, 66*. CRC Press, 66.

Fearnley, N., Johnsson, E., & Berge, S. H. (2020). Patterns of e-scooter use in combination with public transport. *Transport Findings*.

Fearnley, N. (2020). Micromobility–regulatory challenges and opportunities. *Shaping Smart Mobility Futures: Governance and Policy Instruments in Times of Sustainability Transitions*, 169–186.

Fearnley, N. (2022). Factors affecting e-scooter mode substitution. *Findings*, 1–6.

Georgiadis, G., Politis, I., & Papaioannou, P. (2014). Measuring and improving the efficiency and effectiveness of bus public transport systems. *Research in Transportation Economics, 48*, 84–91.

Gössling, S. (2020). Integrating e-scooters in urban transportation: Problems, policies, and the prospect of system change. *Transportation Research Part D: Transport and Environment, 79*, Article 102230.

Grout, C. A., Jaeger, W. K., & Plantinga, A. J. (2011). Land-use regulations and property values in Portland, Oregon: A regression discontinuity design approach. *Regional Science and Urban Economics, 41*(2), 98–107.

Hardt, C., & Bogenberger, K. (2018). Empirical analysis of demand patterns and availability in free-floating carsharing systems. In 2018 21st International Conference on Intelligent Transportation Systems (ITSC) (pp. 1186–1193). IEEE. November 2018.

Hausman, C., & Rapson, D. S. (2018). Regression discontinuity in time: Considerations for empirical applications. *Annual Review of Resource Economics, 10*, 533–552.

Hidano, N., Hoshino, T., & Sugiura, A. (2015). The effect of seismic hazard risk information on property prices: Evidence from a spatial regression discontinuity design. *Regional Science and Urban Economics, 53*, 113–122.

Hollingsworth, J., Copeland, B., & Johnson, J. X. (2019). Are e-scooters polluters? The environmental impacts of shared dockless electric scooters. *Environmental Research Letters, 14*(8), Article 084031.

Hörcher, D., & Tirachini, A. (2021). A review of public transport economics. *Economics of transportation, 25*, Article 100196.

Hsu, Y. C., & Shen, S. (2019). Testing treatment effect heterogeneity in regression discontinuity designs. *Journal of Econometrics, 208*(2), 468–486.

Imbens, G., & Kalyanaraman, K. (2012). Optimal bandwidth choice for the regression discontinuity estimator. *The Review of Economic Studies, 79*(3), 933–959.

Imbens, G. W., & Lemieux, T. (2008). Regression discontinuity designs: A guide to practice. *Journal of Econometrics, 142*(2), 615–635.

Jarboui, S., Forget, P., & Boujelbene, Y. (2012). Public road transport efficiency: A literature review via the classification scheme. *Public Transport, 4*, 101–128.

Johnes, G., & Tsionas, M. G. (2019). A regression discontinuity stochastic frontier model with an application to educational attainment. *Stat, 8*(1), e242. https://doi.org/10.1002/sta4.242

Johnson, A. L., & Kuosmanen, T. (2011). One-stage estimation of the effects of operational conditions and practices on productive performance: Asymptotically normal and efficient, root-n consistent StoNEZD method. *Journal of Productivity Analysis, 36*(2), 219–230.

Johnson, A. L., & Kuosmanen, T. (2012). One-stage and two-stage DEA estimation of the effects of contextual variables. *European Journal of Operational Research, 220*(2), 559–570.

Jondrow, J., Lovell, C. A. K., Materov, I. S., & Schmidt, P. (1982). On the estimation of technical inefficiency in the stochastic frontier production function model. *Journal of Econometrics, 19*(2–3), 233–238.

Jung, E. (2025). Changing sense of place in privately owned public spaces during the pandemic: Evidence from a regression discontinuity in time design. *Environmental Impact Assessment Review, 110*, Article 107706.

Karlaftis, M. G. (2004). A DEA approach for evaluating the efficiency and effectiveness of urban transit systems. *European Journal of Operational Research, 152*(2), 354–364.

Kawaguchi, D., Naito, H., & Yokoyama, I. (2017). Assessing the effects of reducing standard hours: Regression discontinuity evidence from Japan. *Journal of the Japanese and International Economies, 43*, 59–76.

Kobayashi, L. M., Williams, E., Brown, C. V., Emigh, B. J., Bansal, V., Badiee, J., Checchi, E. M., Castillo, E. M., & Doucet, J. (2019). The e-merging e-pidemic of e-scooters. *Trauma Surgery & Acute Care Open,, 4*(1), Article e000337.

Kuosmanen, T. (2008). Representation theorem for convex nonparametric least squares. *The Econometrics Journal, 11*(2), 308–325.

Kuosmanen, T., & Kortelainen, M. (2012). Stochastic non-smooth envelopment of data: Semi-parametric frontier estimation subject to shape constraints. *Journal of Productivity Analysis, 38*, 11–28.

Lee, D. S., & Lemieux, T. (2010). Regression discontinuity designs in economics. *Journal of Economic Literature, 48*(2), 281–355.

Liu, S., Ermolieva, T., Cao, G., Chen, G., & Zheng, X. (2021). Analyzing the effectiveness of COVID-19 lockdown policies using the time-dependent reproduction number and the regression discontinuity framework: Comparison between countries. *Engineering Proceedings, 5*(1), 8.

Mergoni, A., & De Witte, K. (2022). Estimating the causal impact of an intervention on efficiency in a dynamic setting. *Journal of the Operational Research Society, 73*, 2275–2293.

Mitropoulos, L., Stavropoulou, E., Tzouras, P., Karolemeas, C., & Kepaptsoglou, K. (2023). E-scooter micromobility systems: Review of attributes and impacts. *Transportation Research Interdisciplinary Perspectives, 21*, Article 100888.

Simar, L., & Wilson, P. W. (2007). Estimation and inference in two-stage, semi-parametric models of production processes. *Journal of Econometrics, 136*, 31–64.

Soland, J., Johnson, A., & Talbert, E. (2022). Regression discontinuity designs in a latent variable framework. *Psychological Methods, 28*(3), 691–704.

Thistlethwaite, D., & Campbell, D. (1960). Regression-discontinuity analysis: An alternative to the ex post facto experiment. *Journal of Educational Psychology, 51*, 309–317.

Tovar, B., & Wall, A. (2014). The impact of demand uncertainty on port infrastructure costs: Information for regulators? *Transport Policy, 33*, 176–183.

Tuli, F. M., Mitra, S., & Crews, M. B. (2021). Factors influencing the usage of shared e-scooters in Chicago. *Transportation research Part A: Policy and Practice, 154*, 164–185.

Verma, U., Diamant, A., Imanirad, R., Verma, A., & Razak, F. (2025). Resilience and adaptation: Assessing the effects of COVID-19 on hospital efficiency and quality. Available at SSRN 5396361.

Victorino, T., & Peña, C. R. (2023). The development of efficiency analysis in transportation systems: A bibliometric and systematic review. *Sustainability, 15*(13), Article 10300.

Wang, H. J., & Schmidt, P. (2002). One-step and two-step estimation of the effects of exogenous variables on technical efficiency levels. *Journal of Productivity Analysis, 18*, 129–144.

Wang, K., Qian, X., Fitch, D. T., Lee, Y., Malik, J., & Circella, G. (2022). What travel modes do shared e-scooters displace? A review of recent research findings. *Transport Reviews*, 1–27.

Zhang, W., Meng, J., & Tian, X. (2020). Does de-capacity policy enhance the total factor productivity of China's coal companies? A regression discontinuity design. *Resources Policy, 68*, Article 101741.

Zhuo, C., Xie, Y., Mao, Y., Chen, P., & Li, Y. (2022). Can cross-regional environmental protection promote urban green development: Zero-sum game or win-win choice? *Energy Economics, 106*, Article 105803.