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# USING QUASI-EXPERIMENTAL DESIGNS FOR CAUSAL EFFECTS

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**Purpose:** This paper discusses the concept of identifying the causal effects using quasi-experimental methods and applies this method to investigate the impact of high license fees on the quality of mobile Internet in Poland.
**Design/methodology/approach**: Quasi-experiment design, especially the difference-in-differences method and the interrupted time series design were used to examine the causal effects of spectrum fees in Poland. Data on the quality of mobile Internet in Poland and around the world published by Akamai and data provided by Ookla® under the agreement[1] were used for analysis.
**Findings:** The study did not confirm the impact of high spectrum fees on the quality of the Internet in Poland.
**Practical implications:** The results obtained can help policymakers in Poland and other countries in making decisions on spectrum management.
**Originality/value:** This is the first paper using the quasi-experimental method to examine the effects of the 4G auction in Poland.
**Keywords:** quasi-experiment, difference in difference (DiD), interrupted time series design (ITS), spectrum auction, mobile Internet market.
**Category of the paper:** Research paper.

## 1. Introduction

One of the key issues in scientific research is uncovering causal effects between the analyzed phenomena (Angrist, Piszke, 2009). This issue is particularly important in public policy research. Causal inference supports the evaluation of implemented policies or interventions, like the effects of an aid program or changes in tax law, as well as helps predict the consequences of changing regulations and facilitates policymakers in future decisions.

[1] Data provided by Ookla® based on John Paul II University in Biała Podlaska analysis of Speedtest Intelligence® data from 2017 to 2020. Ookla® trademarks used under license and reprinted with permission.

Identifying the real links between an effect and a cause is quite difficult and connected with many methodological problems. In fact, it is difficult to prove that a given effect (e.g., a decrease in traffic accidents) is the result of specific interventions, such as changes in traffic regulations, rather than the result of other, not included factors. Despite methodological difficulties, a disturbing trend can be observed in empirical research, involving the misuse of the interpretation of the results obtained in terms of causal relationships, including the excessive use of the term "impact" in the titles of research papers (Imai, 2008; Sagan, 2011). It is also quite common, especially in survey research, to use the so-called subjective confirmation of causality, where the existence of causality (e.g., the effects of implementing an aid program) is inferred based on respondents' subjective opinions on the subject, rather than on reliable measurements of specific evaluation metrics (Sagan, 2015).

It is also common practice to draw conclusions on causation based only on the correlation observed between variables. Correlation refers to the situation when changes in one variable co-occur with changes in another variable, which, however, does not necessarily mean that the relationship identified from empirical data is causal. In reality, it may, for example, be the result of a third variable not included in the study (called a confounding factor), which affects both variables causing the correlation between variables to be a spurious relationship. An additional problem in correlation studies is that it is often not possible to determine the direction of the relationship (indicate which variable came first e.g.is the cause). In addition, the same variable can be both cause and effect, i.e. there can be a feedback loop between two variables that interact with each other. For studies involving multiple variables, endogeneity between explanatory variables can also add additional complications for researchers (Shadish, Cook, Campbell, 2002; Sagan, 2011).

The most reliable method of identifying causality is a randomized controlled trial (RCT), which, by manipulating the factor analyzed and random assignment, eliminates the problem of confounding factors and directionality allowing the discovery of causal effects (Coleman, 2019). In medicine they are a natural way of conducting experiments, and are considered the "gold standard", but in the social sciences implementation of RCT is difficult and often even impossible. In such cases, quasi-experimental designs are increasingly used, which under certain conditions, despite undermining the assumptions of a typical experiment, can be as reliable as RCTs (Shadish et al., 2002; Kim, Steiner, 2016).

The paper aims to present the concept of identifying causal effects by the quasi-experimental design and to exemplify this method on the basis of the mobile Internet market in Poland. Quasi-experiment is a relatively new approach in economic studies, so we believe, that our paper can contribute to the spread of this method among Polish researchers. This study is a continuation of the author's research on spectrum auctions (Kuś, 2020, 2022) and the potential impact of high license fees on the mobile Internet market (Kuś, 2023).

In the following part of the paper, the background for quasi-experimental design is presented, and two major statistical techniques used in conducting this type of research are presented: the difference-in-differences method and the interrupted time series design (in single and multiple group versions). Section 4 presents an example of using a quasi-experimental project on the basis of the mobile internet market in Poland

## 2. Quasi-experimental designs as a tool for causal inference

The most appropriate and reliable method for discovering causal relationships is experiment. Unlike correlation and regression analysis, which can only determine the direction and strength of a relationship, experiments can additionally provide insight into how a change in one factor leads to changes in another. By manipulating the factor of interest with other conditions left unchanged, it is possible to see a potential causal factor and have more confidence that what has changed is responsible for the outcome or effect we observed (Coleman, 2019; Shadish et al., 2002).

The basis of causal inference is counterfactual analysis. The counterfactual is something that contradicts facts. In an experiment, we observe what happened to individuals after the analyzed factor (intervention, policy or program) was worked. The counterfactual state is a hypothetical result, that tells what would have happened to the same individuals if they simultaneously had not been exposed to it (if the intervention had not occurred). In reality, however, this alternative (hypothetical) state is never observed, since the same individuals can't be and not be exposed to the intervention at the same time. Consequently, the main task in experimental design is to create reasonable approximations of this physically impossible counterfactual scenario and to understand how it differs from the actual state (Shadish et al., 2002). To do this, it is necessary to identify two groups of participants: an experimental (treatment) group consisting of individuals exposed to the factor or intervention, and a control group which are not exposed to it. The inclusion of a control group captures what the results would have been if the program (policy) had not been implemented (i.e., it identifies the alternative scenario). The effect is the difference between what happened when exposure to the factor/intervention took place and what would have happened if it had not. This simultaneously isolates and tests the effects of one factor and increases confidence that the effect is caused by the analysed factor and not something else (Coleman, 2019).

The most perfect form of experiment is the randomized controlled trial (RCT), the development of which is widely credited to Ronald Fisher (Shadish et al., 2002). Its characteristic feature is the random assignment to groups (e.g., by flipping a coin), which ensures that they are probabilistically similar and increases certainty that observed differences in outcomes between the groups at the end of the experiment are the result of the intervention not to differences between groups that already existed at the beginning of the trial (Shadish et al., 2002).

Despite many advantages of randomized experiments, there are situations in which random assignment or inclusion of control groups is difficult or even impossible. This is the case, for example, with nationwide interventions (involving all individuals), those that have occurred in the past or interventions where ethical, political or logistical constraints exclude random assignment. In such situations, quasi-experimental designs can be an effective way to learn about causal effects (Turner et al., 2021). In these projects, a program or policy is viewed as an "intervention" whose effects are studied in terms of achieving its goals measured by a predetermined set of metrics. Recent innovations allow researchers to treat quasi-experimental design similarly to randomized studies and obtain equally reliable results (Wing, Simon, Bello-Gomez, 2018; White, Sabarwal, 2014).

Quasi-experiments, like RCT projects, are designed to test causal hypotheses and share with them many technical details, such as the common use of control groups and pre-test measurements. A quasi-experimental design, however, by definition lacks random assignment. Assignment to conditions (experimental group and control group) is most often determined by the researcher or is done by the participant's own choice (White, Sabarwal, 2014; Shadish et al., 2002). Unlike traditional experiments, in which an intervention is introduced purposely to observe its effects, quasi-experimental designs are often conducted retrospectively, i.e. after the intervention has been implemented. However, it is always strongly recommended that, if possible, evaluation planning should begin before the intervention, since this method requires pre-intervention data that is not always available post facto

A special case of quasi-experiments are so-called natural experiments, in which a naturally occurring incident, unplanned and uncontrolled for research purposes, such as an earthquake or an unexpected migrant influx, plays the role of the intervention. This incident is independent of the ongoing processes and affects only a portion of the individuals, which is an exogenous source of variation in the dependent variable and provides a naturally occurring contrast between treatment and control groups (Meyer, 1995).

The fact that in a quasi-experiment, participants are not randomly assigned may raise concerns that individuals in the control group may differ from those in the experimental group in several systematic (non-random) ways, other than exposure to the intervention (selection bias). In such situations, the observed differences between the two groups in the indicators of interest (values of the dependent variable) may be due, in whole or in part, to poor matching rather than to the intervention. Thus, when designing a quasi-experimental study, it is necessary to identify a comparison group that is as similar as possible to the experimental group in terms of baseline (pre-intervention) characteristics and also to use an appropriate methodology that corrects for any differences (White, Sabarwal, 2014). This issue will be discussed in the next section.

# 3. Statistical techniques used in quasi-experimental designs

In this section, we will discuss two basic methods of data analysis for measuring causal effects in quasi-experimental projects.

## 3.1. The Difference-in-Differences method

One of the most well-known and oldest techniques used to estimate causal relationships based on quasi-experiments is the difference-in-difference (DiD) method. This method is currently employed in econometrics, but the underlying logic called the controlled before-and-after study, was applied as early as the 1850s by John Snow to study the causal effects of the spread of the cholera epidemic in London (Goldman-Bacon, 2021).

DiD design is typically used to estimate the effects of interventions or changes in policies (e.g., tax policy). The essence of this method is to compare the differences in outcomes (measured by a predefined indicator - Y) before and after the intervention between the individuals exposed (the experimental group) and those who are not exposed to it (the control group).

The great attractiveness of the DiD method comes from its simplicity, as well as its potential to avoid many problems related to endogeneity that often arise when studying causal effects (Meyer, 1995). DiD designs can be used in settings where interchangeability between experimental and control groups cannot be assumed, making this method a good approach for quasi-experimental studies, where randomization at the individual level is not possible for various reasons. Due to intuitive methodology, this approach is widely used in research on public policy, health care, economics and many others, including for evaluating the effectiveness of European Union support programs (Bondonio, 2021).

One of the most widely cited publications using the difference-in-differences method is Card and Krueger's study on the effect of increased minimum wage on employment in fast-food restaurants in New Jersey (Card, Krueger, 1994). Using neighbouring Pennsylvania as a natural control group (the minimum wage was not changed in that state), they revealed that, contrary to classical economic theories, raising the minimum wage did not increase employment. These results contributed to the spread of quasi-experimental research using the DiD method in economics, leading David Card to receive the A. Nobel Prize in 2021.

The DiD project provides a stronger estimate of impact than a simple comparison of differences in outcomes between the treatment and control groups after the intervention. Simple before-and-after outcome comparisons can be affected by temporary trends in the outcome variable or other events that occurred between the two periods compared. The difference-in-differences method removes biases in post-intervention period comparisons between the experimental and control groups that may be due to permanent differences between these groups (including differences that may have already existed at the beginning of the study), as well as biases from comparisons over time in the test group that may be due to trends caused by other causes (Difference-in-Difference Estimation, 2023; White, Sabarwal, 2014).

The main limitation of the DiD method is the parallel trend assumption, which states that if there had been no intervention, the difference between the experimental and the control group would have been constant, i.e. it would have remained the same in the post-intervention period as in the pre-intervention period. This allows DiD to include unobserved variables that are assumed to remain constant over time (White, Sabarwal, 2014).

Trend parallelism is by nature unobservable in DiD projects. This assumption is intended to determine the alternative (counterfactual) scenario, i.e., what would have happened if the intervention had not occurred. Although there is no statistical test to verify this assumption, in situations where we have observations at multiple time points, it can be helpful to visually control the data and examine trends before the intervention to see if exposed and unexposed groups followed similar trajectories This step is not always possible, as the DiD method compares only two points data: before and after the intervention, and does not require data from multiple time points.

Most often, a linear econometric model is used to estimate the difference in differences. To isolate the analyzed effect it controls independent changes within groups over time (effects of confounding variables) and between groups (baseline differences). In the standard version with two variables, the DiD method corresponds to the following econometric multivariate regression model (Sagan, 2011):

$$Y_i = \beta_0 + \beta_1 X_i + \beta_2 Z_i + \beta_3 X_i Z_i + \xi_i \tag{1}$$

where:

Y – dependent variable (outcome variable),

X – dummy variable describing the state: (X = 0 – before intervention, X = 1 – after intervention),

Z – dummy variable representing the group (Z = 0 – control group, Z = 1 – experimental group).

The ordinary least squares (OLS) method is commonly used to estimate model parameters. The estimate of the effect of interest, i.e., those changes that are associated with both groups (experimental and control) and state (before and after intervention) is the coefficient β3 standing by the interaction $X_iZ_i$. It determines the difference in slope (difference in differences) between the two groups before and after the intervention, i.e. it estimates how much more the dependent variable increased (or decreased - depending on the sign of the coefficient) in the experimental group compared to the control group. The remaining parameters of the model (1) have the following interpretation: the parameter β0 estimates the average value of the dependent variable in the control group before the intervention, β1 determines the difference in the outcome before and after the intervention in the control group, and β2 estimates the difference between the groups in the pre-intervention period.

The adoption of the regression method makes it possible to verify the model and assess its internal consistency. By including additional explanatory variables, confounding factors can also be controlled, making DiD estimation more robust to errors.

### 3.2. Interrupted time series design

The DiD design discussed in the previous section usually refers to a controlled "before-and-after" study in which the outcome is measured at one baseline (before the intervention) and one time point after the intervention, or the average outcomes are compared before and after the intervention, but where the variable representing time is not included in the model. The counterfactual in this method is estimated from the control group only, and it is assumed that both groups' trends are parallel. Although some approaches can be used to increase the similarity of the two groups, the assumption of parallel trends in the DiD design is not always verifiable, which may raise concerns about the validity of the results obtained.

An alternative approach to studying causal effects (effects of interventions) is the interrupted time series design (ITS), which uses multiple sequential observations before and after an intervention and takes time into account. To use this method, data on the outcomes of interest (the dependent variable) spread over equally spaced intervals (e.g., months, quarters) are required.

The simplest version of the ITS design (named single group ITS) does not include a control group and is based on the following multiple regression model (Linden, Arbor, 2015):

$$Y_t = \beta_0 + \beta_1 t + \beta_2 X_t + \beta_3 t X_t + \xi_t \tag{2}$$

where:

$Y_t$ – dependent variable (outcome variable) measured at each equally distributed time point *t* (t = 1, 2, …, N),

t – variable determining the time since the start of the study (t = 1, 2, …, N),

$X_t$ – dummy variable representing the intervention (Xt = 0 before the intervention, Xt = 1 after the intervention).

The coefficients of the model defined by formula (2) have the following interpretation: β0 specifies the initial level of the outcome variable Y, β1 estimates the slope until the introduction of the intervention, β2 represents the change in the level of the dependent variable observed immediately after the introduction of the intervention (compared to the counterfactual) and β3 represents the difference between the slope of the outcome before and after the intervention. Evidence of the causal effect of the intervention is provided by the significance of the parameters β2 (immediate effect) and β3 (over time effect).

The counterfactual scenario in the interrupted time series model without a comparison group is estimated by extrapolating the pre-intervention trend, and it is assumed that the trend will remain unchanged in the absence of intervention. Since observations are made in the same population, differences between groups do not create a problem, and the strict time structure makes it possible to control for underlying trends and temporally changing confounders. The main threat to interrupted time series designs without a control group is the possibility of co-occurring events with the intervention (historical or instrumental effects) (Shadish et al., 2002).

If it is possible to compare the results of the intervention group with a control group, the internal validity of model (2) is further strengthened due to the ability to control for confounding variables. Such an approach is referred to as comparative interrupted time series design (CITS) or multiple group ITS design, and is represented by the following econometric model (Linden, Arbor, 2015):

$$Y_t = \beta_0 + \beta_1 t + \beta_2 X_t + \beta_3 t\, X_t + \beta_4 Z + \beta_5 t\, Z + \beta_6 X_t Z + \beta_7 t\, Z X_t + \xi_t \qquad (3)$$

Additional elements of this model compared to model (2) are the dummy variable Z representing group assignment (Z = 0 for the control group and Z = 1 for the treatment group) and the interaction of this variable with the other variables.

Figure 1 shows a graphical representation of the ITS method, which can help in understanding this project. The coefficients of the lower line (β0 to β3) represent the trajectory of the control group before and after the intervention, while the coefficients of the upper line (β4 to β7) represent the experimental group. Specifically: β4 and β6 represent the difference in the level of the dependent variable Y between the test group and the control group before and immediately after the intervention, respectively; β5 represents the difference in the slope (trend) of the outcome variable between the experimental group and the control group before the intervention; and β7 represents the difference between the groups in the slope (trend) of the outcome variable after the start of the intervention compared to before the intervention (i.e., it determines the effect of the intervention on the outcome`s growth rate).

In the CITS design, the impact of the program is estimated by testing whether the treatment group differs from the baseline trend by a greater amount than the control group during the observation period. This design is a stronger one than the DiD because it controls differences between experimental and comparison groups concerning their baseline levels and growth. In addition, the CITS design has more rigorous data requirements than the DiD design. It needs data for at least four equally spaced time points before starting the intervention to estimate the baseline trend (Somers et al., 2013).

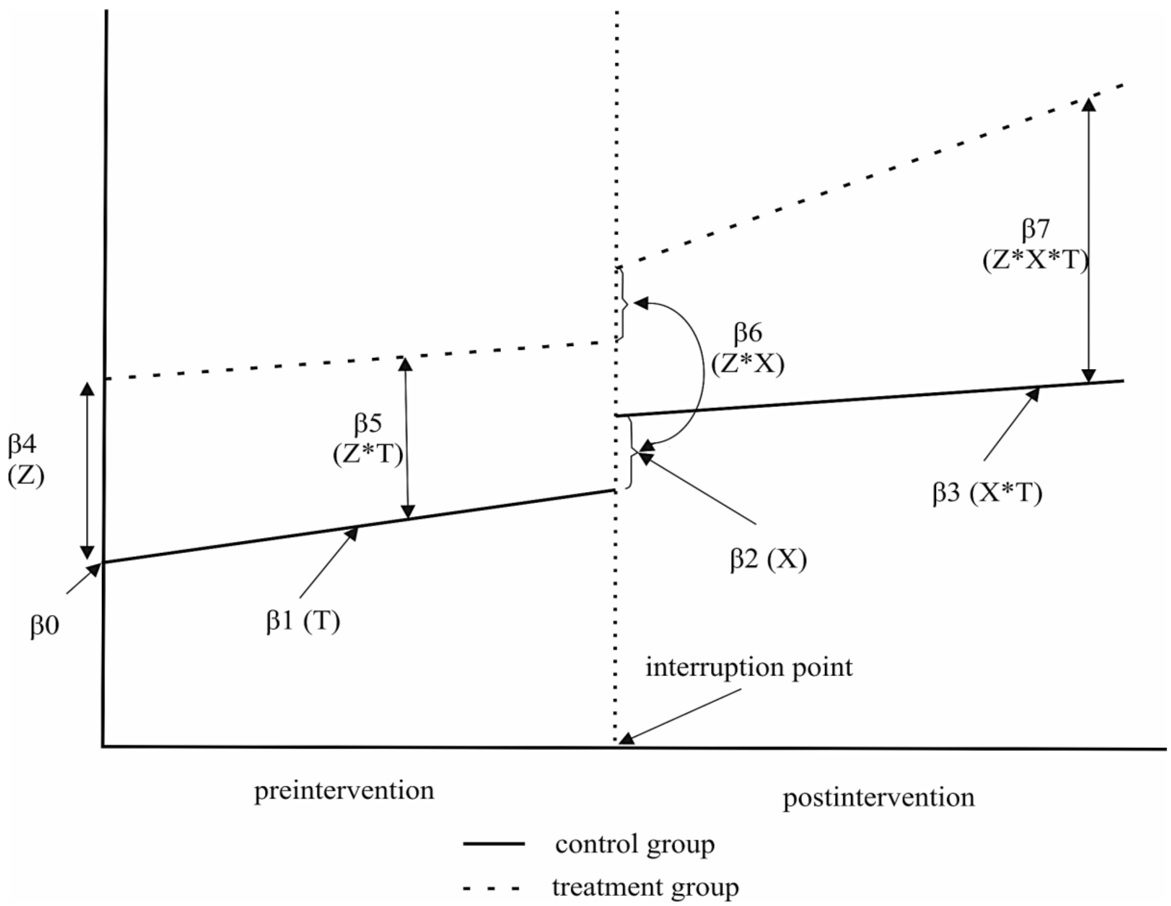


**Figure 1.** Graphical presentation of ITS.

Source: (Linden, Arbor, 2015).

A key assumption of the interrupted time series design with a control group is, as in the DiD method, the parallel trends assumption, which in practice means that variables not included in the study affect both treatment and control groups similarly. Failure to meet this assumption can lead to unwarranted conclusions about the causal effects of intervention. In the case of random assignment, similarity between individuals in the two groups is highly probable, but in the case of quasi-experimental designs, it cannot be excluded that the observed differences are due to prior disparities between groups.

The main advantage of the CITS design is the ability to test comparability between groups with respect to the variables included in the model. Of special importance in the context of the parallel trends assumption are the two parameters β4 and β5, which allow us to determine whether the experimental and control groups are comparable in both the level and trajectory of the outcome in the pre-intervention period. To reduce the risk of bias, researchers can try to approximate the randomization process by finding control groups that display similarity with the test group in terms of observed variables before the intervention. One approach to finding comparable control groups among potential candidates is an iterative process in which each control group is compared separately to the experimental group using model (3). Those groups for which the β4 and β5 parameters do not display statistical significance can be considered credible (Linden, Arbor, 2015).

An additional benefit of the CITS method is its robustness to co-occurring events, like other potentially competing interventions (historical effects) or changes in outcome measurement methodology. If the co-occurring events affect the experimental and comparison groups to the same extent, then the CITS methodology allows a reliable estimate of the treatment effect (Kim, Steiner, 2016).

## 4. Application of quasi-experimental methods in the case of the Polish mobile Internet market

In this section, we will apply three quasi-experimental methods presented in Section 3 to evaluate the effects of high spectrum prices on the Polish mobile Internet market. The main role in our study will be played by the Polish auction of frequencies necessary for LTE services, which ended in October 2015. Spectrum auction was an unusual event in the Polish telecommunications market, as this form of spectrum allocation was implemented in Poland for the first time. The importance of the event was also reinforced by the fact that, in light of the poor quality of fixed-line Internet in Poland, the auction was an opportunity to meet the goals of the European Digital Agenda, which was to provide all Europeans with broadband Internet access by 2020 (EC, 2010).

Four major mobile operators (i.e., Orange, P4, T-Mobile and Polkomtel) and two others: NetNet and Hubb Investment participated in the auction. It had a turbulent course and lasted a very long time compared to other spectrum auctions in the world (the main bidding included 513 rounds), largely due to significant failures in the auction rules (Kuś, 2020). The lack of credibility of bidding and the inability to enforce the bids made by auction participants encouraged speculative bidding and translated into the level of prices achieved. The total revenue from the auction amounted to more than PLN 9 billion and was one of the highest in Europe, which raised concerns about the negative effects of high spectrum prices on the Polish mobile market and consumers (Kuś, 2020, 2023).

Concerns about the results of the Polish LTE auction fit into the discussion about the impact of high license fees on the wireless market development, which has been going on for years in the academic and industry literature (Kuś, 2023). Two opposing views are presented in this discussion. Proponents of standard economic theory believe that license fees are sunk costs, so they are irrelevant to the development of the mobile market, in particular, they do not affect pricing and investment decisions (Garrison, Noreen, Brewer, 2010; Kwerel, 2000; Buchheit, Feltovich, 2011). On the other hand, some researchers and industry representatives point out some weaknesses in the sunk cost argument concerning mobile markets, claiming that high amounts paid by operators can slow down network development and hurt consumers (Bauer 2003; GSMA, 2019, ITU, 2019).

Due to the discrepancy in positions on this issue, many empirical studies are being conducted on the real-world links between license fees and the outcome of mobile markets. Much of this research employs standard correlation and regression analysis, which, as noted in Section 1, can lead to invalid conclusions about causal relationships. Given that we will use the new quasi-experimental approach to investigate the causal effects of interest. The Polish LTE auction will be treated as a natural experiment to examine whether high license prices have had a negative impact on the quality of mobile services in Poland. As a measure of service quality, we have adopted the download speed rate, which will play the role of the dependent variable in our quasi-experiment. In addition, to capture the causal effects, the Polish outcomes were compared with the results in other countries (with a global trend), which will constitute a kind of control group. Significant changes in Poland's position compared to other countries after the spectrum auction will support the thesis that high spectrum prices harmed the mobile market in Poland.

Data on download speed comes from two international diagnostic companies: Akamai and Ookla. These were quarterly data covering the period of 2013-2020 i.e. the period before and after the auction. The research period is relatively short, which is a weakness of the study but is nevertheless determined by the nature of the topic undertaken, particularly by rapidly changing technologies. The lower limit of the timeframe is due to the availability of data, while the upper limit is due to the fact that since 2020 mobile services in many countries have already been provided in 5G technology based on other, dedicated to this technology frequency bands. In Poland, this band was not allocated until 2023, i.e. much later than in other countries, which could be one of the important reasons for the discrepancy in the quality of mobile services in Poland and around the world, and could wrongly suggest that the decreasing quality of mobile services in Poland compared to other countries is due to the high prices of 4G spectrum.

Table 1 presents the estimation results of the multivariate regression models corresponding to the three statistical techniques presented in Section 3, i.e. DiD (column 2), single ITS (column 3) and the ITS with a control group (column 4). In brackets are p-values for the Student's T-test verifying the significance of the relevant explanatory variable. Estimation was done by the OLS method using the Statistica software, adopting a significance level of 0.05.

**Table 1.**
*The results of the estimation of multiple regression DiD and ITS models*

| **Variable (effect)** | **Method** | | |
|---|---|---|---|
| | **DiD** | **single ITS** | **ITS with a control group** |
| t | --- | **0.36 (0.04)** | 0.36 (0.147) |
| X | **18.29 ($p<0.01$)** | 0.841 (0.46) | 0.27 (0.87) |
| Z | 0.26 (0.94) | --- | 0.21 (0.91) |
| t*X | --- | **1.13 ($p<0.01$)** | **1.15 ($p<0.01$)** |

Cont. table 1.

| | | | |
|---|---|---|---|
| X*Z | 1.15<br>(0.79) | --- | 1.15<br>(0.61) |
| t*Z | --- | --- | 0.02<br>(0.97) |
| t*X*Z | --- | --- | -0.03<br>(0.93) |
| Intercept | 4.03<br>(0.11) | **2.09**<br>**(0.04)** | 1.98<br>(0.15) |
| | R2=0.57<br>F=25.68<br>P<0.01 | R2=0.98<br>F=760.21<br>P<0.01 | R2=0.98<br>F=336.53<br>P<0.01 |

Note. Statistically significant results are in bold.

Source: own elaboration.

The results of the F-tests confirm the overall significance of the models (p-value in all cases meets the condition of $p < 0.01$) and the coefficients of determination (R-squared) confirm their good fit to the data. The independent variables in our models explain from 57% (DiD) to 98% of the variation in the dependent variable (ITS with the control group). Based on the DiD model we can conclude, that before the intervention the global average download speed was 4.03 Mb/sec while in Poland it was 0.26 Mb/sec higher. However, the results of the T-test indicate that these results were not statistically significant ($p > 0.05$ in both cases). The coefficient corresponding to the interaction term X*Z is also no significant ($p = 0.79$), indicating that there is no significant impact of high auction prices on the quality of the Internet in Poland. The significance of the parameter on the variable X denoting the intervention allows us to conclude that global Internet quality after the auction was significantly higher than before it (by 18.29 Mb/sec on average, $p < 0.01$), which is in line with the general trend showed, that the quality of the Internet is constantly improving due to the development of technology.

Applying the ITS design, in turn, it was estimated that at the beginning of the study period, the download speed in Poland was 2.09 Mb/sec (a statistically significant outcome, $p = 0.04$) and in the pre-intervention period it increased every quarter by an average of 0.36 Mb/sec. The model did not confirm a significant change in Internet quality in Poland immediately after the intervention (the estimated increase of 0.84 Mb/sec was not statistically significant, $p = 0.46$). However, the significance of the parameter at interaction t*X ($p < 0.01$) indicates that the speed of Internet in Poland increased faster after the auction than before, confirming the causal effect of the intervention over time. It should be noted, however, that this model does not take into account a control group, i.e. it does not take into account changes in Internet quality worldwide. Thus, based on such a model, we cannot determine whether the changes in Internet quality in Poland after the auction were the result of the intervention, or whether they were due to global trends, according to which Internet quality around the world is continuously improving. Before drawing definitive conclusions, therefore, it is necessary to analyze the CITS model, which compares the results in Poland with a comparable control group, and see whether the Polish results differ from the baseline trend more than the results in the control group.

The results of the estimation of the ITS model with the control group, presented in Table 1 (column 3), do not confirm the impact of 4G auction outcomes on Internet quality in Poland. The only statistically significant parameter turned out to be the parameter standing at the interaction t*X. However, this parameter refers to the control group (see, Section 3.2) and indicates that the increase in download speeds in the control group after the intervention was higher than before it. There were no significant differences between the results in Poland and the world immediately after the auction ($\beta 6 = 1.15$, $p = 0.61$) and after the intervention ($\beta 7 = -0.03$, $p = 0.93$). The rate of increase in download speed in Poland was slightly lower compared to global changes ($\beta 7 = 0.03$), but the difference was not statistically significant ($p = 0.93$).

Noteworthy is also the fact that the implemented control group was comparable to the experimental group at baseline ($\beta 4 = 0.21$, $p = 0.91$) as well as in trend ($\beta 5 = 0.02$, $p = 0.97$). It indicates that the parallel trends assumption was met and the control group defined in the study was reliable (Linden, Arbor, 2015).

## 5. Summary

The concept of using quasi-experimental design to study causal effects was discussed in this article. Particular attention was paid to two statistical techniques that serve this purpose: the difference-in-differences and interrupted time series methods.

The paper also presents an application case study of a quasi-experimental design to investigate the potential impact of high license fees on the quality of mobile services in Poland, contributing to the broad discussion on the relationship between spectrum cost and wireless market development, that has been going on for years in the scientific and industry communities. Given the lack of a consistent position on this issue, analyzing specific markets, especially markets that have faced high license fees, can be a valuable contribution to the discussion of the sunk cost argument in relation to mobile markets.

The use of a quasi-experimental method made it possible to conclude about the causal effects of the Polish 4G auction. For this purpose, econometric multivariate regression models were estimated, in which the dependent variable was a variable representing the quality of mobile Internet in Poland. Our research did not confirm the thesis that high license costs affected the quality of the Internet in Poland. Although the estimation results of the ITS model without the control group indicated a significantly higher quality of the Polish Internet after the auction, taking into account global trends, it turned out that the observed changes were not significantly different from those registered in the control group, and finally cannot be considered an effect of the auction outcome. Our findings are consistent with the sunk cost argument in relation to mobile markets, which may provide an argument in the discussion between policymakers and the industry community. They also make room for further in-depth research, including, for example, the potential impact of spectrum prices on the financial situation of service providers and the level of investment in the network.

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