

EVALUATING THE EFFICIENCY OF THE SPECIAL TAX REGIME

DIHA CITY

by

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## ACKNOWLEDGMENTS

The author dedicates this work to his wife, who supported him in his controversial decisions, which he believed to be right. Her encouragement was invaluable during the author's most challenging period of life.

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## LIST OF ABBREVIATIONS

**DC** Diia City

**PIT** Personal Income Tax

**SSC** Social Security Contribution

**ML** Military Levy

**ECT** Exit Capital Tax

**CIT** Capital Income Tax

**ST** Single Tax

**NDC** Non-Diia City

**DiD** Difference-in-Difference

**PSM** Propensity Score Matching

**ATT** Average Treatment Effect on the Treated

**ROA** Return on Assets

**EU** European Union

**OECD** Organisation for Economic Co-operation and Development

**IHS** Inverse Hyperbolic Sine

**COGS** Cost of Goods Sold

**NN** Nearest Neighbour

## CHAPTER 1. INTRODUCTION

In mid-2021, the Ukrainian government introduced the Law of Ukraine “On Stimulating the Development of the Digital Economy in Ukraine.” It was only the first step in implementing the new Diia City (DC) tax regime. The real possibility of registration under the new tax regime required other laws and resolving technical and staff issues, and only on February 15, 2022, the first DC company was registered.

The main benefits of joining the new tax regime include: lower tax rates and the possibility of legal tax optimization. The government proposed:

### Labor Taxes:

- 5% Personal Income Tax (PIT) instead of the regular 18%;
- Social Security Contribution (SSC)—22% on the minimum wage as taxable base (instead of on the entire wage, taking into account the maximum base);
- 1.5% Military Levy (ML), increased to 5% since January 2025;

### Two options for Corporate Tax:

- 9% Exit Capital Tax (ECT);
- or 18% Corporate Income Tax (CIT).

So, at first glance, the benefits of DC are clearly defined. However, the real choice between being in DC or not is not so straightforward: in IT, there are many methods of tax avoidance, which include a legal possibility to reduce taxes, as opposed to tax evasion, which is illegal. Such tax avoidance methods start from the simplest use of sole

entrepreneurs (“self-employed”) paying the Single Tax (ST) to reduce labor expenditures to more complicated techniques for decreasing CIT, including base erosion and profit shifting (thin capitalization, tax havens, and so on). And if we look closer at what non-Diia City (NDC) companies pay, we realize that the ST for employees, who are nominal sole entrepreneurs, is 5%, the SSC is the same as for DC’s companies—22% of the minimum wage, and the MV is also the same. Of course, the CIT for NDC is much higher—18%—compared to the 9% ECT for DC, which also has to be paid only when a company distributes the profit. However, using tax avoidance methods makes it possible to pay CIT even less, but it requires some effort and time. Of course, a higher risk of attention from tax authorities is also present.

One of the goals of this study is to estimate the efficiency of the new tax regime, which was actually implemented by the Ukrainian government less than two weeks before the full-scale Russian invasion. So, we have the new tax initiative, the results of which can be distorted by a significant external factor.

The base of this study is the dataset from the annual financial reports of IT companies that can use the new tax regime. The observation period includes years before and after implementing DC, with firms that joined DC or are still working under the traditional tax system.

The estimation approach is based on Difference-in-Difference (DiD) modeling, which gives instruments for controlling the impact of the factor of war. The idea behind this is that we can control this negative factor because it is present for both groups of firms. The model also includes other variables, which present IT companies' efficiency and size.

The other significant element of methodology is Propensity Score Matching (PSM). I observe an essential variety of companies by size or financial measures. And some of the DC companies could be more successful even before implementing the new tax regime. So, their further growth of profitability can be caused by historical prepositions, not only

by choosing the DC tax regime. For managing it, I have to define two comparable groups of companies before the special tax regime DC was implemented: treated and control. The assumption is, that for similar DC and NDC companies, the probability of choosing the DC tax regime was the same. So, further growth of profit measures must be caused by a status DC or NDC company.

The Average Treatment Effect on the Treated (ATT) and DiD modeling imply the positive effects on Profit Margin, Return on Assets (ROA), and Probability Profit. The ATT results differ slightly from DiD models, but the findings remain applicable due to the differences in the estimation method.

The analysis results demonstrate evidence of the efficiency of the new tax regime DC, as indicated by improved profitability measures of treated firms. It suggests that this tax initiative is successful and leads to increased commercial opportunities for IT companies. However, the future of such tax initiatives is under discussion due to the increasing trend of curtailing tax initiatives among European Union (EU) states, largely driven by policies of the Organisation for Economic Co-operation and Development (OECD).

The thesis is structured as follows: the IT industry overview and review of related studies are presented in Chapter 2, while discussion of the methodology and data used in the study can be found in Chapter 3 and Chapter 4, respectively. Chapter 5 presents the obtained results and their interpretation. Finally, conclusions and recommendations are discussed in Chapter 6.

## CHAPTER 2. INDUSTRY OVERVIEW AND RELATED STUDIES

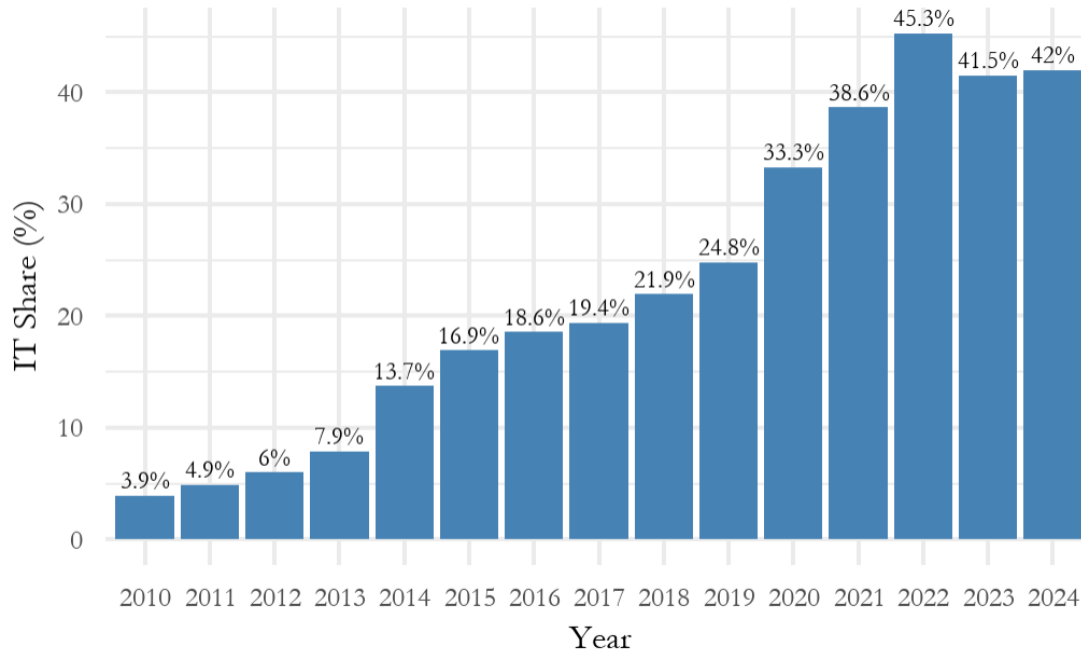
### 2.1. Ukrainian IT Industry Overview

The government introduced the special tax regime DC in 2022 for the long term—it was not a short experiment. We can ensure this by the duration of the rule for the most significant part—tax incentives—25 years. The idea behind such a long-term tax initiative was that investment needs tax stability, and if some rules exist for more than two decades, they have to be predictable and preferable for investors.

The fiscal initiative of a special tax regime for IT companies is not new. Similar tax initiatives can be observed, for instance, in Europe: IT Box in the Netherlands, Knowledge Development Box in Ireland, and mRiik in Estonia. The rules are different, but the main idea is the same—fewer restrictions and lower tax rates for profit shifting.

Ukraine is also highly interested in developing the IT sector. IT exports account for approximately 565 million USD monthly, and the IT share in total service exports is essential, as shown in Figure 1.

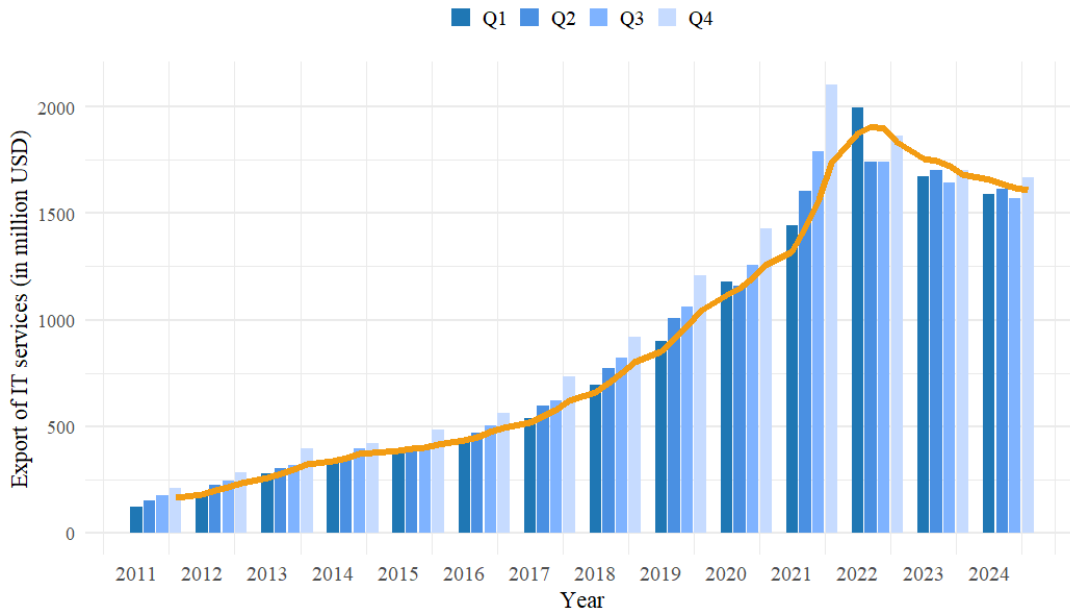
Figure 1. Annual IT-share in total export of services in Ukraine (2010-2024)



Source: Own presentation based on data provided by the National Bank of Ukraine

The strong increasing trend of IT exports was visible from 2011 to 2021, however, after 2022, we observe a decrease year-on-year (Figure 2). Of course, it was caused by the full-scale russian invasion when the economy struggled in the circumstances of war, and some of the investment was relocated to safer countries. It is more convenient for an IT cluster where assets are typically intangible and staff are highly qualified and well-paid, which can allow them the possibility of relocation.

Figure 2. Quarterly export of IT services in Ukraine (2011-2024)



Source: Own presentation based on data provided by the National Bank of Ukraine

DC was introduced in the same year, 2022, so it creates exceptional circumstances where the observation of profitability or volume of IT exports does not show the real efficiency of the new tax regime. We must consider the factor of war in our research when assessing our results and conclusions.

However, even during the full-scale russian invasion, the Ukrainian TOP-10 IT companies by revenue in 2024 demonstrated a total minimal growth of 1.5%, as shown in Table 1.

Table 1. TOP-10 digital companies by revenue and growth in 2024

<i>Ranking</i>	<i>Company name</i>	<i>Revenue 2024,</i> <i>thousands UAH</i>	<i>Revenue 2023,</i> <i>thousands UAH</i>	<i>Revenue</i> <i>growth</i>
1	GlobalLogic Ukraine	11,662,493	11,417,253	<b>2.1%</b>
2	EPAM Systems	11,349,613	12,616,190	<b>-10.0%</b>
3	EPAM Digital	7,526,997	6,001,623	<b>25.4%</b>
4	LUXOFT SOLUTIONS	5,453,813	5,876,080	<b>-7.2%</b>
5	Intellias	4,063,180	4,334,182	<b>-6.3%</b>
6	SoftServ Technologies	3,831,223	2,327,244	<b>64.6%</b>
7	FINTECH BAND	3,706,273	5,578,131	<b>-33.6%</b>
8	HIGHLOAD SOLUTIONS	3,223,149	1,027,179	<b>213.8%</b>
9	Ciklum	3,204,136	3,830,753	<b>-16.4%</b>
10	Tietoevry Create Ukraine	3,064,129	3,232,206	<b>-5.2%</b>
		<b>57,085,006</b>	<b>56,240,841</b>	<b>1.5%</b>

Source: Opendatabot, YC.Market

This table demonstrates a general view of the main players in the IT market, but for a full picture, it requires further analysis. For instance, the second and third places by revenue in 2024 go to EPAM Systems and EPAM Digital, which represent the same business structure, but in two different entities. SoftServ Technologies is just six, but this business also has different entities with the same main beneficiary in Malta: SoftServ Digital, SoftServ Dynamics, SoftServ Industry, SoftServ-Development, and it is not even a full list of SoftServe companies.

For deeper exploration, it is better to look at the other ranking, based on the number of employees, as shown in Table 2. In this ranking, I use the commercial name (or brand), as in the original source, not the name of entities from the official state sources.

Table 2. TOP-10 digital companies by employees (by January 2025)

<i>Ranking</i>	<i>Company</i>	<i>Employees</i>
1	EPAM Ukraine	9,570
2	SoftServe	7,279
3	GlobalLogic Ukraine	5,660
4	Ajax Systems	3,900
5	Luxoft	3,200
6	Genesis	2,815
7	Evoplay	2,613
8	ZONE3000	2,242
9	Intellias	2,210
10	DataArt	2,172

Source: jobs.dou.ua

DOU.UA experts received information about the number of employees directly from such companies, these are total (aggregate) numbers for entire companies, not by subunits. The ranking here looks different, and I observe three well-defined leaders: EPAM Ukraine, SoftServe, and GlobalLogic Ukraine.

## 2.2. Related Studies

In this section, I examine the existing studies on evaluating tax initiatives that used econometric analysis. Fiscal initiatives are a popular research topic due to their importance for businesses and policymakers.

Kronfol and Steenbergen (2020) emphasize that more than half of developing countries have introduced tax initiatives in the form of tax holidays or reduced CIT rates. Their analytical report emphasizes that the effectiveness of such tax initiatives is not guaranteed if there are problems with the judicial system, logistics, and access to markets. So, given the limitations of the war, parallels can be drawn with the Ukrainian DC, which was precisely implemented before the full-scale russian invasion.

Zwick and Mahon (2017) study how the US government attempted to increase private investment using tax simulations. One way was to give taxpayers the possibility of “bonus” depreciation. The research methodology is based on the DiD model using data from 2001 to 2012 for approximately 120,000 firms. Such a model was useful because it allowed for the exploration of two periods: before and after the new tax rules were introduced. Thus, Zwick and Mahon (2017) compare and evaluate the efficiency of implementing the tax initiative for the treatment group compared with the control group.

As a result, Zwick and Mahon (2017) found that “bonus” depreciation does not have an equal influence on profitability for all treated companies. Successful entities could utilize such a preference to reduce their tax base for CIT, while other companies did not achieve significant benefits. This result is consistent with the logic of calculating the tax base for CIT, where depreciation expenses decrease this base and, consequently, the tax burden. Another finding is that small firms are more likely to respond to a decrease in the tax base than large firms. These gains are particularly evident when the period of generating new cash flows is minimal and the tax initiative does not merely assume benefits in the long run.

Klemm and Van Parys (2012) presented one additional critical point regarding the efficiency of tax initiatives based on experience of developing countries. The authors examined various tax initiatives, primarily including investment allowances, accelerated depreciation, and tax holidays, in 47 countries over a 20-year period. The primary objective was to assess the effectiveness of these approaches from the perspective of attracting foreign direct investment. The methodology was based on a combination of models for choosing which outperforms, including OLS, fixed effects (Within Groups), the Difference Gaussian Mixture Model, and the System Gaussian Mixture Model. As a result, the system outperforms in terms of robustness of estimators and suggests that investment allowances and accelerated depreciation have no significant impact or a minimal one on foreign direct investment, whereas tax holidays have a significant influence on it. This leads to competition in tax initiatives between countries in terms of the mechanisms that work.

Another related study, presented by Angrist and Pischke (2008), examines taxable US veterans' earnings from 1988 to 1991. The comparison of naïve method and matching and regression estimates highlights issues in evaluating the difference in earnings between white veterans and white nonveterans, as well as for nonwhite veterans. The naïve method simply shows that both groups of veterans earn more than non-veterans. However, after adjusting for covariates or regression estimation, the difference in means decreased for non-white veterans and even became negative for white veterans. The reason for such a gap in the naïve method is that only high school graduates with good scores were selected for US military service. So, they were well-educated and successful even before joining the US army, and if we control for this covariate to create two comparable groups of persons, the results become totally different.

However, the goal for each study is not only to resolve technical and methodological issues. While it is necessary for modelling, comprehensiveness is achievable if we explain why some initiatives create new opportunities for entities and how they use them. Angrist and Pischke (2008) mentioned this good point. The authors highlight that modelling must be consistent with explaining why the tax initiatives create new opportunities for entities.

## CHAPTER 3. METHODOLOGY

The choice of the methodology is grounded on the existing studies and the dataset design. My data comprises four essential parts: before and after the implementation of DC for two groups of companies, namely the treated and non-treated groups. Some financial statement items from this data are omitted. Also, in 2022, we had the biggest shock for the Ukrainian economy—the start of a full-scale war and a significant decrease in all economic sectors, excluding the military industry. Therefore, I must consider the impact of these factors when constructing my methodology.

I want to investigate how companies' performance was affected by joining DC. In particular, I model the relationship between profitability, DC participation, and control variables:

$$\textit{Profitability} = f(\textit{DC}, \textit{control variables}) \quad (1)$$

First, I discuss my dependent variables, which measure companies' profitability. Then, I provide an overview of the modeling approach, specifically the DiD and PSM methodologies.

### 3.1. Profitability Measures

A simple comparison of profits for DC vs. NDC companies does not provide a comprehensive picture of the efficiency of implementing the new tax regime. So, more advanced profitability measures can include three indicators:

1. Log Profit Margin—the log-transformed ratio of profit to revenue, which assesses how revenue growth influences profit.

2. Log ROA—the log-transformed ratio of profit to the sum of current and non-current assets (or total assets). This indicator measures the efficiency of asset utilization.
3. Probability Profit—binary indicator of profitability (1-profit, 0-loss), which shows the probability of receiving profit after joining the DC tax regime.

Together, these indicators can represent the profitability measures of joining the DC and evaluate the depth of the new tax regime's impact. The first two indicators capture efficiency relative to revenue and assets, the third defines the likelihood of generating a profit.

For robustness, I also use two Inverse Hyperbolic Sine (IHS) or arcsinh transformed variables, which consider negative and zero profit values (Appendix A), unlike the log-transformation:

1. IHS Profit Margin—the arcsinh-transformed ratio of profit margin. But for large and positive values, it can be interpreted as a natural logarithm (Bellemare and Wichman, 2020). The IHS is useful for my skewed financial data, because profit and loss can be significantly different for small and large companies. The IHS is calculated as follows:

$$IHS(Profit\ Margin_{it}) = \ln\left(\frac{Profit_{it}}{Revenue_{it}} + \sqrt{\left(\frac{Profit_{it}}{Revenue_{it}}\right)^2 + 1}\right). \quad (2)$$

2. IHS ROA—the arcsinh-transformed ratio of ROA. This indicator estimates the efficiency of using assets according to the following formula:

$$IHS(ROA_{it}) = \ln\left(\frac{Profit_{it}}{Total\ Assets_{it}} + \sqrt{\left(\frac{Profit_{it}}{Total\ Assets_{it}}\right)^2 + 1}\right). \quad (3)$$

However, using the IHS transformation is not a complete solution for handling negative and zero values due to a challenge in interpretation (World Bank, 2021). The reason is that the direct interpretation of IHS-transformed variables leads to biased results, because my variables estimate not only the positive effect for IT companies with profits, but also capture transitions from losses to profits. Additionally, the IHS-transformed variables are sensitive to the units used in the estimation. Therefore, to ensure correct interpretation, I employ the smearing retransformation proposed by Duan (1983) to determine if my assessment of the positive effect of the DC tax regime is overly optimistic. The formula is as follows:

$$\sinh(x) = \frac{e^x - e^{-x}}{2} \quad (4)$$

where:

$x$  – is a component defined by IHS transformation.

Therefore, it can be useful to compare Log and IHS-transformed variables for additional robustness.

### 3.2. Implementing the DiD Model

The DiD model can be a good choice because two groups of companies (DC and NDC) had the same economic and non-economic challenges. Therefore, I can mitigate shocks that affect all companies by adding the NDC group and evaluating the efficiency of implementing the new tax regime for DC firms.

The first model that I estimate is as follows:

$$\begin{aligned} \text{Log}(\text{Profit Margin}_{it}) = & \beta_0 + \beta_1 DC_i + \beta_2 post_t + \beta_3 (DC_i * post_t) + \\ & + \beta_4 \log \text{Employee}_{it} + e_{it}. \end{aligned} \quad (5)$$

where:

$DC_i$  – binary variable, taking on value 1 if company is in DC, and 0 otherwise;

$post_t$  – binary time variable taking on value of 1 for periods after introduction of DC and 0 before DC was introduced;

$DC_i * post_t$  – DiD estimator;

$Log Employees_{it}$  – number of employees for controlling the size of companies.

The other two models use different dependent variables: Log ROA and Probability Profit, keeping the RHS variables unchanged. As a robustness check, I also estimate the first two models using the IHS-transformed variables for Profit Margin and ROA.

The variable  $post_t$  captures the general impact on profitability of IT companies after the introduction of the DC tax regime, regardless of whether they are DC or NDC companies. If the coefficient on this variable is significant, it implies that Profit Margin increases or decreases for all companies after 2022.

The DiD estimator has a special function: it measures the effect of the new tax regime's treatment on the company's profitability. The statistically significant and positive coefficient means that residence in DC leads to higher profitability. Basically, it demonstrates the efficiency of implementing the new tax regime.

It is worth noting that the DiD model works correctly only if the treatment and control groups have similar characteristics. This means that they would generally develop in the same way without treatment. However, it can be tricky to define for companies that work in different IT industry niches, have varying sizes, histories, and other factors. So, it can be useful for the robustness of results to add to the model two components controlling fixed effects:

$\mu_i$  – unobserved heterogeneity between firms (as industry niche);

$\lambda_t$  – time-variant shocks.

So, the modified model is as follows:

$$\text{Log}(\text{Profit Margin}_{it}) = \beta_0 + \beta_1(\text{DC}_i * \text{post}_t) + \mu_i + \lambda_t + e_{it}. \quad (6)$$

The other components ( $\text{DC}_i + \text{post}_t$ ) are dropped in the model with fixed effects.

The underlying assumption behind DiD is parallel trend assumption. In our case we have parallel trends conditional on firms' size measured by revenue. Use of control variables in the DiD model is possible when assumption about unconditional parallel trends may not hold.

### 3.3. Propensity Score Matching (PSM)

The main risk is that IT companies that chose a special tax regime DC could be more profitable and successful even before introducing the new tax regime. Therefore, I might find that their profitability grew, but it would still occur even without implementing DC. It violates the random treatment assumption in DiD-modeling.

Considering the following risks, I must analyze two comparable, in terms of observed characteristics, groups of companies that chose to use DC and those that did not. For this purpose, I can use PSM. The idea behind it is to define propensity score covariates using data from the pre-DC period for comparing two groups of companies: those treated (DC) and those not treated. When modeling the probability of joining the DC, I must consider the company's size and financial metrics, including the number of employees, annual revenue, net profit, liabilities, and current and non-current assets. After that, it is possible to define the propensity score for each company and choose only companies with

similar results for further analysis. Consequently, the starting position before the possibility of choosing a special DC regime would be very close for each company.

I defined the following propensity score covariates for the future model: Log Revenue, Log Employee, IHS Profit, Log Total Assets, Log Liabilities, and Code (the industry niche, as a factor):

$$\begin{aligned}
 \text{Probability in DC} = f(\log(\text{Revenue}_{it}), \\
 \log(\text{Employees}_{it}), \text{IHS}(\text{Profit}_{it}), \log(\text{Total Assets}_{it}), \log(\text{Liabilities}_{it}), \text{Code}_{it})
 \end{aligned}
 \tag{7}$$

Another important consideration is defining the matching method in relation to my dataset and goals. Caliendo and Kopeinig (2008) emphasize that the Nearest Neighbour (NN) matching is the most straightforward matching estimator, but with the risk of bad matches if measures of similar companies are far apart. However, I suppose that this issue may not be critical due to the large sample size of my dataset, which comprises nearly 5,000 firms. So, the possibility of defining the nearest control firm with close measures is high.

When calculating the effect of DC using PSM, I need to use more than one control firm per treated individual. Possibly, a 3-to-1 ratio is good enough and leads to higher robustness of the model, reducing variance.

After calculating the results for DC and NDC companies, the difference in profitability must be averaged to obtain the ATT, using the post-DC part of the data for the two comparable groups of companies after PSM. This allows more solid conclusions about the actual effect of tax initiatives, controlling for factors associated with self-selection into treatment.

According to Angrist and Pischke (2008), the ATT for the first indicator, Log Profit Margin, can be calculated as follows:

$$ATT = E[\text{Log}(\text{ProfitMargin}_i^{DC}) - \frac{1}{|M(i)|} * \sum_{j \in M(i)} \text{Log}(\text{ProfitMargin}_j^{NDC})]. \quad (8)$$

where:

$E$  – average difference between DC and NDC Profit Margins;

$\text{Log}(\text{ProfitMargin}_i^{DC})$  – the value of Log Profit Margin for  $i$  number of treated firm DC;

$\text{Log}(\text{ProfitMargin}_j^{NDC})$  – the value of Log Profit Margin for  $j$  number of non-treated firm NDC;

$M(i)$  – the number of matched control firms NDC.

The same approach is used for the other performance indicators described in Section 3.1.

It is essential to note that applying PSM does not deny the possibility of implementing the DiD model. After PSM, I can use it for two new comparable groups of companies (DC and NDC), with improvements. Angrist and Pischke (2008) emphasize that variables defined prior to the outcome variable are commonly good controls, because the treatments did not affect them. Consequently, they shouldn't be used in the outcome equation as independent variables. Therefore, I consider excluding the variables used in PSM from the final DiD model to avoid “overcontrol”. This consideration may be particularly relevant for size-firm control variables, which are suitable covariates in PSM due to the high skewness of financial data and the interdependence between company size and participation rates in DC.

## CHAPTER 4. DATA

For my research, I use the annual financial statements of IT companies and cumulative information from Diia.City Registry. It is the whole population of companies that work with code 62.01 Computer programming, 58.29 Publishing other software, and all other codes from related spheres: 62.02, 62.03, 62.09, 63.11, 63.12, 63.91, 63.99, and 58.21. The companies with these main codes represent the Ukrainian IT sector and have the possibility to choose between DC and NDC.

For the study, I can use annual financial statements with the maximum legal observation period: 2019-2024. The reason that my dataset cannot start earlier than in 2019 is due to changes to Part 2, Article 14 of the Law of Ukraine “On Accounting and Financial Reporting in Ukraine,” which was introduced on January 1, 2019: “Financial statements of enterprises are not considered commercial secrets, are not confidential information, and do not fall under restricted access information, except in cases provided by law. The prohibition on disseminating statistical information does not apply to financial statements”. For comparable data, I select only companies that began their work no later than 2019 and were still active as of 2024. As a result, I get a balanced panel.

During my research, I worked with three different reporting forms: complete financial reports and financial reports for small and micro companies. For instance, a company with 300 million hryvnias in revenue, 40 staff members, and rented assets can use financial reports typically used by small companies, which have fewer financial indicators (Part 2, Article 2 of the Law of Ukraine “On Accounting and Financial Reporting in Ukraine”). This might be a common case, since in such a business, other staff members can work like self-employed (sole entrepreneurs). However, it is possible to manage this issue: according to National Accounting Standard (NAS) 25 “Simplified Financial Statements,” there are accounting rules on how these financial statement line items are converted for simplicity in small and micro financial report forms. Therefore, I need to

convert the data from both the complete and small financial report forms in the same manner and obtain the financial statement line items.

As a result of preliminary preparation, I use a dataset of annual financial reports from 5,013 IT companies to test my hypothesis about the efficiency of the new tax regime. For the study, I can observe financial statements from 2020 to 2024, received from Opendatabot, one of the largest Ukrainian companies that works with open data. Not all the data from the financial reports is provided. My preliminary dataset comprises the following three groups of variables:

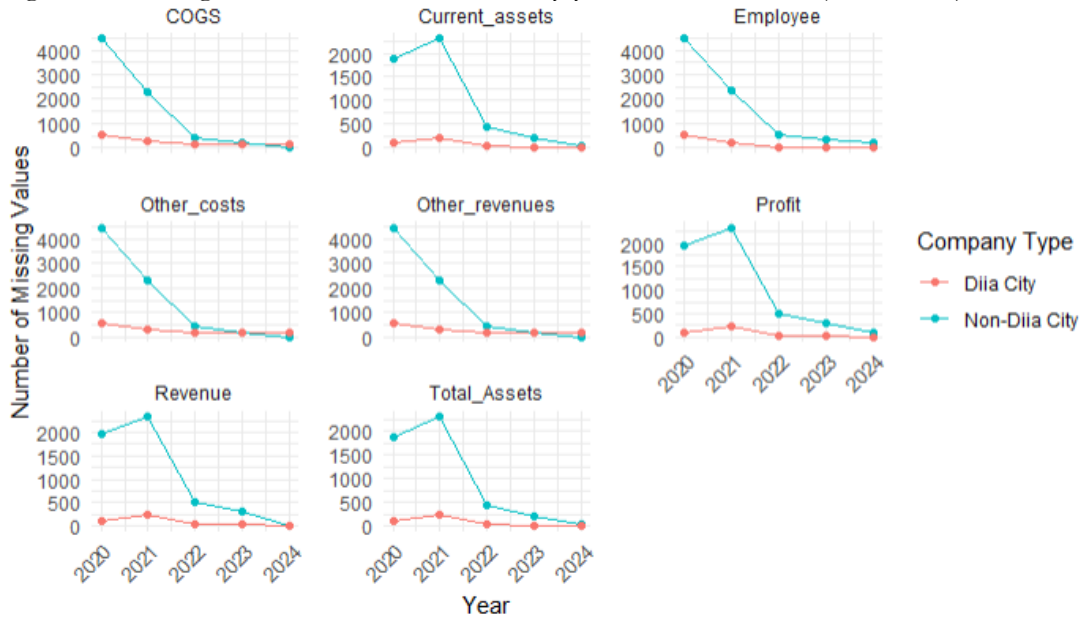
- Company identification components: Company ID, Code, Registration Year, Registration DC Date;
- Balance sheet data: Current Assets, Non-Current Assets, Total Assets, Liabilities, Employees;
- Income statement data: Revenue, Cost of Goods Sold (COGS), Other Costs, Other Revenues.

The last two income statement items (Other Costs and Other Revenues) are not provided separately in most reports. However, they were intentionally grouped: the reports for small companies do not include information about, for instance, distribution or administrative expenses, so it would be impossible to compare different companies with significant differences.

After conducting a preliminary analysis, I identified several issues with the financial reports, including omitted values, technical errors, and the potential for incorrect reports without an audit. For instance, part of the 2021 reports was omitted due to circumstances of war because Ukrainian companies faced difficulties with their annual reports, which were required to be presented by the end of February 2022. The government provided an option of not reporting without penalty.

Another problem is present in the financial reports in 2020: the number of employees is absent, according to different forms of reporting, and it is impossible to extract this value from the database. Due to technical issues, information about COGS, Other Revenues, and Other Costs has also been omitted for this particular year (Figure 3).

Figure 3. Missing financial statement items by year and DC status (2020-2024)

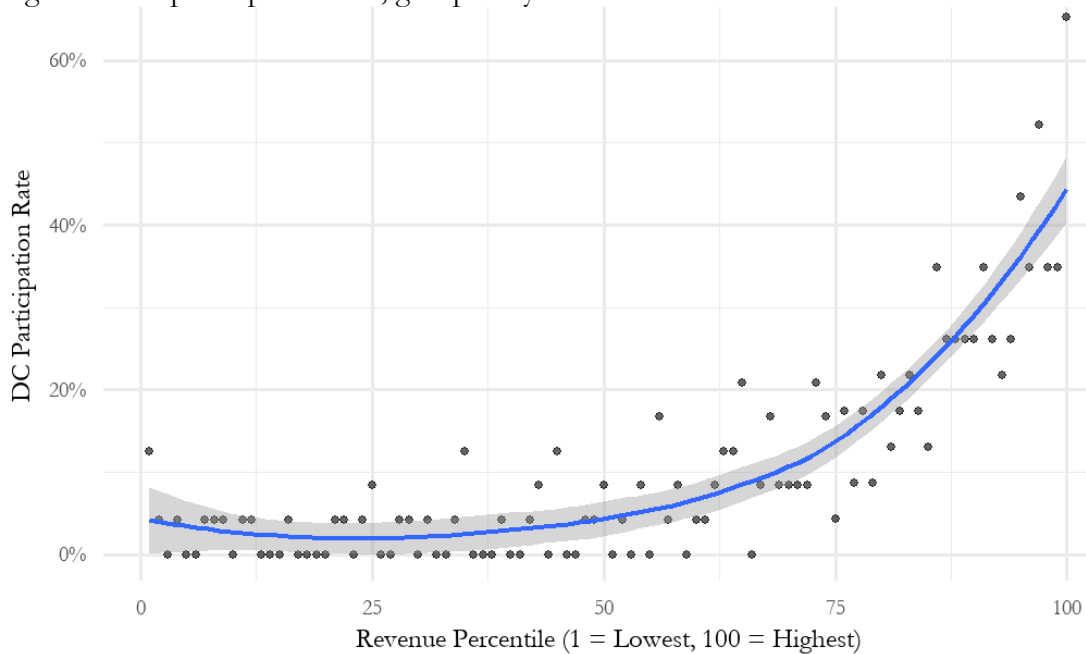


As we see, the closer the values in the dataset are to the present, the better the data is provided. For both types of firms, data for all variables has improved essentially since 2022. In 2024, nearly all the data was available.

Additionally, DC's financial reports are more proportionally well-presented than NDC's. Possibly, the reason is one of the requirements for a DC company: the average salary must be at least the equivalent of 1,200 euros in hryvnia. It can be unaffordable for the smallest and most unsuccessful IT companies, so DC companies can have, on average, more revenue, consequently, a higher probability of employing full-form financial reports with more requirements and a more qualified accounting staff for performing them.

To test my hypothesis of higher revenue for DC companies, I ranked all companies by revenue in 2021, when the new tax regime had not yet been implemented, and grouped them into percentile categories. For each group, the number of DC companies was calculated and presented in the share of the total number of companies, as shown in Figure 4.

Figure 4. DC participation rate, grouped by revenue in 2021



I observe a convex trend line with a gray area around (95% confidence band), which shows a higher DC participation rate associated with increasing revenue. IT companies with higher revenue are more likely to choose DC. Therefore, the new tax regime was more favorable for successful companies with a higher market share. If the number of employees defines a company's size, the dependence has the same direction but is not so pronounced, as shown in Appendix B.

In summary, my dataset contains omitted values, which are more frequently found at the beginning of the observation. DC companies provide more comprehensive financial

reports due to their larger mean size, which is defined by either revenue or the number of employees (Appendices C and D).

To better understand the properties of the dataset, I defined the values for the three main financial statement items (Total Assets, Profit, and Revenue) across the years of observation (2020-2024) and DC status, but for the data after the PSM application. The table shows the values for 195 DC companies.

Table 3. Descriptive statistics for 195 DC companies (2020–2024), in thousands UAH

<i>Indicator</i>	<i>Year</i>	<i>Mean</i>	<i>Standard deviation</i>	<i>Min</i>	<i>Max</i>
<b>Revenue</b>	2020	83,941	170,792	38	963,655
	2021	104,522	243,030	0.2	1,978,390
	2022	121,880	279,700	4	2,368,377
	2023	172,289	497,354	176	5,578,131
	2024	211,388	485,124	998	3,831,223
<b>Profit</b>	2020	9,552	46,426	-16,139	502,425
	2021	15,226	106,054	-117,734	1,400,962
	2022	16,923	106,280	-72,320	1,414,821
	2023	29,951	227,972	-31,107	3,142,822
	2024	25,325	98,485	-117,570	1,150,613
<b>Total Assets</b>	2020	36,782	84,050	1	737,411
	2021	48,534	125,567	26	1,126,180
	2022	62,411	157,957	148	1,178,764
	2023	84,359	217,099	44	1,859,755
	2024	98,066	218,564	16	2,085,379

I observe changes in the distribution of all financial indicators across the years: higher means, standard deviations, and maximum values. Generally, DC companies have been growing from 2020 to 2024, with a significant increase in profit since 2022, which can preliminarily suggest improved efficiency in profitability measures.

The next step is to explore the same financial indicators and descriptive statistics parameters for 507 NDC companies, matched after PSM, as shown in Table 4.

Table 4. Descriptive statistics for 507 NDC companies (2020–2024), in thousands UAH

<i>Indicator</i>	<i>Year</i>	<i>Mean value</i>	<i>Standard deviation</i>	<i>Min</i>	<i>Max</i>
<b><i>Revenue</i></b>	2020	75,637	237,399	20	3,420,477
	2021	80,759	273,130	20	4,063,443
	2022	90,759	350,109	1	4,819,083
	2023	94,393	337,399	0.1	4,334,182
	2024	80,023	286,362	0.1	4,063,180
<b><i>Profit</i></b>	2020	3,623	14,975	-61,430	126,893
	2021	3,903	19,189	-178,105	207,750
	2022	4,745	28,933	-162,848	339,257
	2023	7,210	44,284	-69,010	845,286
	2024	5,431	29,819	-67,675	457,570
<b><i>Total Assets</i></b>	2020	32,142	87,631	5	1,302,296
	2021	35,393	110,937	32	1,767,531
	2022	47,406	157,813	1	2,029,257
	2023	53,252	188,928	1	2,836,392
	2024	55,411	196,251	1	3,085,017

As for DC companies, while Revenue was growing across the years, I observed higher mean, standard deviation, and maximum values. However, with the other two indicators, the picture is different: after a period of growth from 2020 to 2023, I observe a decline in 2024. The preliminary results of NDC’s descriptive statistics can suggest lower profitability measures compared to DC companies (Table 4).

## CHAPTER 5. RESULTS

### 5.1. Evaluation of the Possibility of Using DiD Models

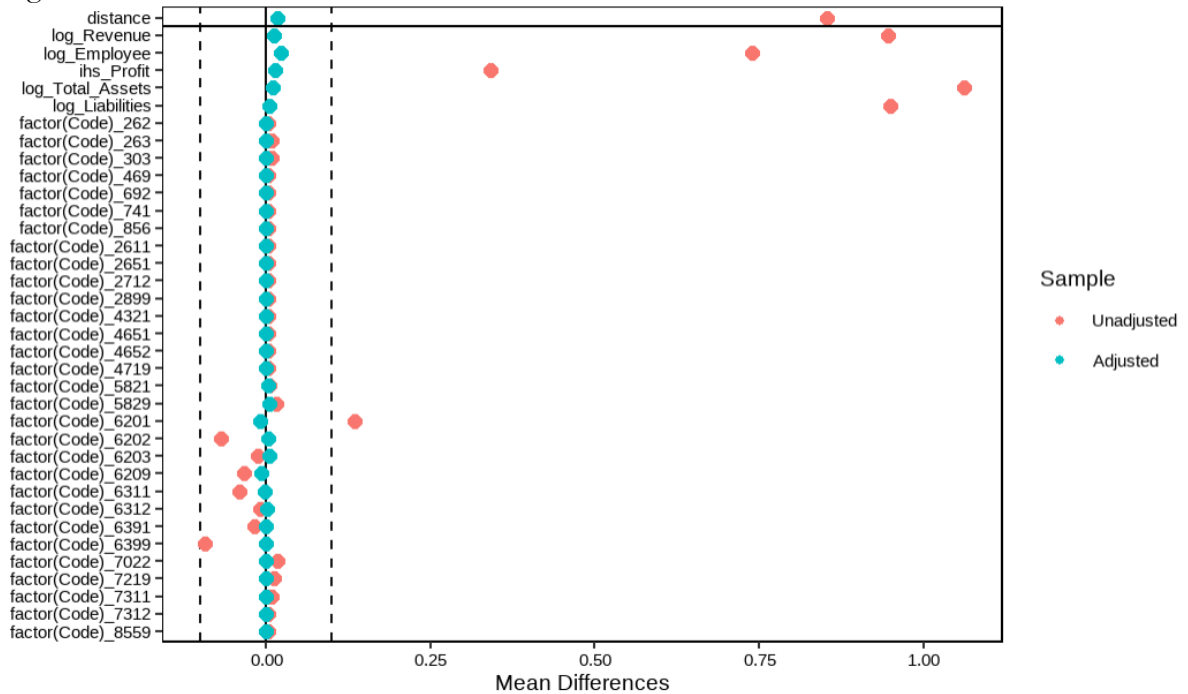
The results of the descriptive statistics indicate a need for improvement in the strategy of this study. I found that IT companies more often choose the special tax regime DC if their size, as defined by revenue or number of employees, is larger. Further research without considering this moment leads to distorted results (Appendix E).

Under these circumstances, I must begin my analysis by using PSM to identify two comparable groups of companies that had the same conditions before the implementation of the new tax regime.

### 5.2. PSM and ATT

The result of the matching is shown in Figure 5.

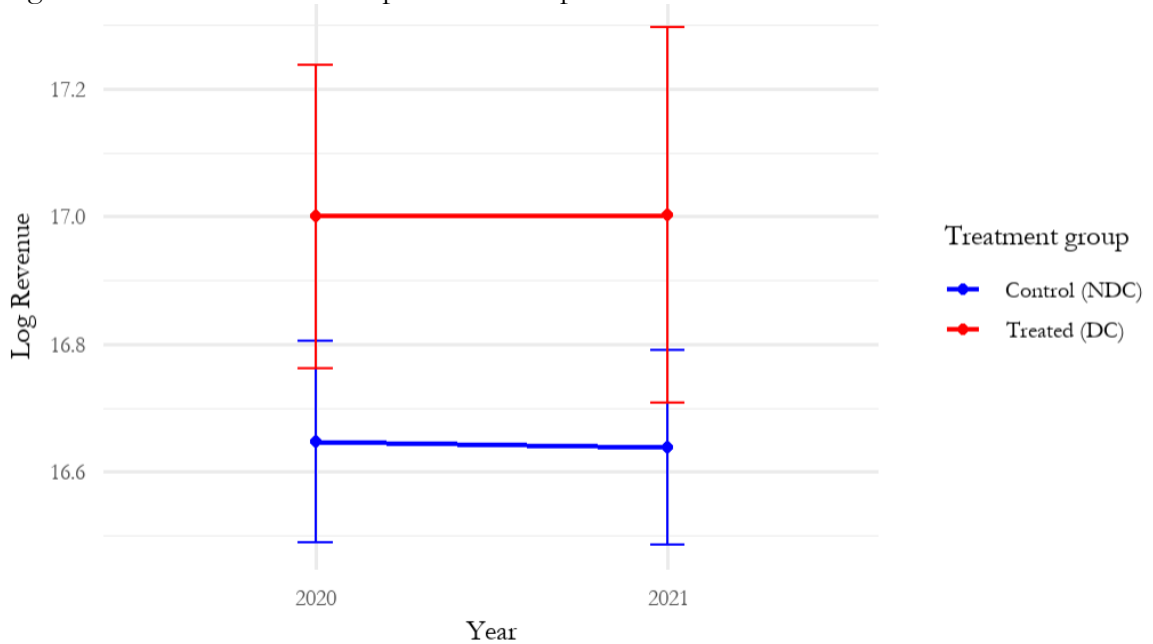
Figure 5. Covariate balance



Seven propensity score covariates were out of the critical measures  $[-0.1, 0.1]$  of the standardized mean differences before matching. After matching, all points are in defined measures, which means that 195 DC and 507 NDC companies are comparable in such covariates. So, NN matching shows applicability for the study.

The next step is to check the visualization of parallel log-revenue trends. Figure 6 demonstrates minimal fluctuation of lines from parallel.

Figure 6. Parallel trends in the pre-treatment period



So, the covariate balance after applying PSM and holding parallel trends in the pre-treatment period suggests the possibility of defining ATT. To assess the efficiency of the new tax regime, I use three main profitability measures (Log Profit Margin, Log ROA, and Probability Profit) and two additional measures (IHS Profit Margin and IHS ROA), discussed in Chapter 3. The results of bootstrapped ATT assessments with 1,000 replications for robustness are in Table 5.

Table 5. ATT for profitability measures

<i>Indicator</i>	<i>ATT</i>	<i>SE</i>
<b>Log Profit Margin</b>	0.364***	0.082
<b>Log ROA</b>	0.496***	0.076
<b>Probability Profit</b>	0.041***	0.019
<b>IHS Profit Margin</b>	0.122***	0.016
<b>IHS ROA</b>	0.075***	0.025

*Note: \*\*\*-significance at <1% level. The IHS-transformed variables are shown after applying the smearing coefficients*

The results demonstrate that all profitability measures for treated IT companies increase after joining DC, and their coefficients are highly significant at the <1% level. After implementing DC, Profit Margin increases by 36.4% and ROA by 49.6%.

For IHS-transformed variables, applying the smearing factors for retransformation does not alter the positive direction of DC's effect. The IHS Profit Margin and IHS ROA, which account for losses, confirm this: the first increases by approximately 12.2% under the DC tax regime, and the second grows by approximately 7.5%.

So, I observe a gap between the coefficients determined for IHS-transformed and log-transformed variables, mainly due to methodological differences in their calculation. However, in addition to the difficulties related to IHS transformation, which I mentioned in Section 3.1, I suggest another reason: profitable DC companies can receive full tax benefits due to the possibility of using ECT, whose tax base is defined by profit, whereas DC companies with losses cannot. Therefore, profitable DC companies receive relatively more tax benefits, consequently, their profitability may be further improved.

The coefficient of the Probability Profit does not need adjustments and demonstrates the positive effect of implementing DC. For a company under DC, the probability of receiving profit increases by 4.1%.

### 5.3. DiD Regression Models

As I mentioned in Section 3.3, applying PSM does not eliminate the possibility of using DiD regression models. Thus, this is another method for estimating the efficiency of the new tax regime and comparing the results with the “directly” defined ATT. I applied DiD regression models with year fixed effects to take into account the time-variant shocks, and clustered standard errors at the company level to account for heterogeneity (Table 6).

Table 6. DiD regression models for profitability measures

<i>Indicator</i>	<i>Log Profit Margin</i>	<i>Log ROA</i>	<i>Probability Profit</i>	<i>IHS Profit Margin</i>	<i>IHS ROA</i>
DiD estimator	0.269* (0.113)	0.560*** (0.107)	0.080** (0.026)	0.195*** (0.029)	0.124** (0.033)
Observations	2,721	2,721	3,387	3,376	3,387
Benjamini–Hochberg test	0.017	0.000	0.003	0.000	0.001
R <sup>2</sup>	0.012	0.013	0.015	0.012	0.010

*Note: \*\*\* -significance at <1% level, \*\* -significance at 1% level, \* -significance at 5% level. The IHS-transformed variables are shown after applying the smearing coefficients*

The results are slightly different than those in Table 5 due to fixed effects, but clearly define the positive effect of joining DC. The DiD regression models indicate that the Log Profit Margin increased by approximately 26.9% under the DC tax regime and the Log ROA by 50.6%. The IHS-transformed variables after applying the smearing factors for retransformation also demonstrate the positive direction of profitability measures: IHS Profit Margin increases by 19.5% and IHS ROA by 12.4%. The Probability Profit for companies under DC increases by 8%.

Unlike in Table 5, the significance for the five profitability measures differs, but remains acceptable and does not fall below the 5% level. The robustness of this finding is demonstrated by the coefficients of the Benjamini–Hochberg test, which are lower

than the critical p-value. It means that even after controlling the False Discovery Rate, I can suggest that my positive results did not occur randomly. So, they are not false discoveries.

The DiD regression models explain only 1-2% of the variation in the dependent variable, but this can be acceptable: I aim to define only the causal effect of DC, not the overall forecast of Profit Margin, ROA, and Probability Profit.

However, for robustness, I must validate the results and find evidence that the results were not achieved due to the predisposition of more successful IT companies.

I can assume that my DiD regression models missed some unobserved trend behind implementing the DC tax regime, which would lead to a distorted result. I can check this by using placebo tests: create some hypothetical treatments in the wrong year of DC implementation (for instance, 2021) and for random groups (30-70% of the data sample). The received coefficients must be insignificant because my model has to demonstrate the effect of actual DC implementation (Table 7).

Table 7. Placebo DiD regression models for profitability measures

<i>Indicator</i>	<i>Log Profit Margin</i>	<i>Log ROA</i>	<i>Probability Profit</i>	<i>IHS Profit Margin</i>	<i>IHS ROA</i>
DiD estimator	0.114 (0.143)	-0.016 (0.147)	0.013 (0.033)	-0.013 (0.019)	-0.008 (0.035)
Observations	512	512	600	599	600
R <sup>2</sup>	0.001	0.000	0.002	0.003	0.003

*Note: \*\*\* -significance at <1% level, \*\* -significance at 1% level. The smearing coefficients are not applied to insignificant DiD estimators*

The DiD estimators became insignificant. However, it is just one test, so I ran it 1,000 times. As a result, the shares of significant outputs were just 5.4% for the DiD estimator of Log Profit Margin, 4.1% for Log ROA, 4.6% for the Probability Profit, 4.2%

for IHS Profit Margin, and 3.3% for IHS ROA, which provides evidence that the treatment produces a real effect on profitability measures.

Therefore, for analysis, I matched two comparable groups of IT companies: the treated (DC) and control (NDC) groups. Applying the PSM was necessary due to a defined higher DC participation rate for firms of larger size, which violates the random treatment assumption. After composing two groups with the same ability to join DC by applying NN, I defined the nearest neighborhoods in each cluster, using weights for the NDC companies. The two estimation models, ATT and DiD, yield significant results at the 5% level, indicating a positive effect on three main and two additional profitability measures for the treated group compared to the non-treated.

The results are comparably close for log-variables: 36.4% (ATT) and 26.9% (DiD) for Profit Margin, and 49.6% and 56% for ROA. The Probability Profit is 4.1% (ATT) and 8% (DiD). Such results can be considered acceptable due to the differences in the methodologies employed. The additional IHS-transformed variables, used for robustness, also demonstrate a positive effect of implementing DC after applying smearing factors. Additionally, I performed a robustness check using the Benjamini–Hochberg and placebo tests.

Together, the results provide evidence that the implementation of the new tax regime has a positive effect on the profitability measures for the treated group under DC (Appendix F).

## CHAPTER 6. CONCLUSIONS AND RECOMMENDATIONS

In this study I looked at the effect of participation in DC on IT companies' profitability. Overall, the results imply a positive effect of introducing the special tax regime DC on companies' performance. It leads to a higher Profit Margin, ROA, and increases the possibility of generating profit. However, receiving such evidence required a careful analysis of each step during the study.

For the study, I used the entire dataset of financial statements from IT companies that had the possibility of joining DC. However, as the author, I would highlight that most of the dataset couldn't be used due to omitted important financial statement items. It was more typical for earlier years of observation, but it was also affected by the issues in annual reporting at the beginning of the full-scale russian invasion. Consequently, one of the suggested improvements for a prospective study in this area is to collect a dataset with at least a longer observation period for more accurate analysis, due to the suggestion that all companies, which use open data sources, deal with the same dataset, and omitted financial statements items do not exist at all.

The results of modeling suggest that implementing the DC special tax regime by the Ukrainian government is efficient, as it has resulted in a reduction in the tax burden for IT companies. It also carefully suggests the competitiveness of the Ukrainian special tax regime in comparison to similar European tax initiatives. For business community, this study provides evidence of the efficiency of joining DC which is seem to be associated with a higher profitability.

However, I would pay attention to the fact that in separate cases, being in DC does not obviously lead to higher profitability compared with NDC's companies, if they use tax avoidance methods, which are defined by OECD (2024-2025). It is essential for understanding the alternative to joining DC.

The OECD describes typical tax avoidance schemes that have been developed over the last few decades and have also been introduced into Ukrainian businesses. Of course, such work aims not to share these activities for implementation, but to popularize them: if a method is well-known, it will not be effective in the future. The country used in the scheme will be defined as a low-tax jurisdiction or country where special legal structures are introduced for companies that, in reality, exploit tax optimization opportunities.

The first statement about low-tax jurisdictions is clear – it is commonly referred to as tax havens. The second statement about special legal structures is less widely known. Generally, some countries can be considered non-tax havens in the traditional sense, for example, the Netherlands, but they offer the opportunity to register a company as such a legal structure as a Commanditaire Vennootschap. This form of registration is typically used for tax optimization by utilizing intangible assets—the royalty income received by such companies is taxed at a 0% rate (PwC, 2025). It is also a good opportunity for IT companies, which often have a large number of such assets. Ukrainian IT is not an exception in this case.

Therefore, I suggest that the advantages of implementing DC, as described in my study, are not absolute evidence that joining DC is the best choice for any Ukrainian IT company.

Additionally, I would like to emphasize that my study provides evidence, based on historical data, regarding the effectiveness of implementing the special tax regime DC. But what about the future of DC? The DC's preferential tax rules must remain unchanged for at least 25 years from the date of implementation, but external factors may alter this perspective.

Assuming that Ukraine aims to join the EU at least in the medium-term future, it is necessary to note that most EU members are part of the OECD or are candidates for accession. Some OECD rules are established by the European Commission and must be

implemented among EU member states. As I mentioned, the OECD describes tax avoidance methods, and one of the components here is that the recommended effective CIT rate is generally defined as not lower than 15%. This is significantly higher than 9% for ECT, the Ukrainian equivalent of CIT, which presents an opportunity for DC companies. Therefore, in a medium-term perspective, we must determine whether the special tax regime DC violates this rule. What can be the future tax policy of the Ukrainian government if this violation is defined? Can the ECT rate change?

Of course, the OECD does not apply the rules directly in particular countries, but its recommendations are highly incorporated into national tax laws. One of the trends among EU states is the gradual tendency to narrow preferential tax regimes. In line with the OECD's guidance, EU states restrict them or have announced plans to phase them out. Therefore, suggested future work should not only address the effectiveness of the DC but also examine the fundamental components of Ukrainian tax policy in the context of further European integration.

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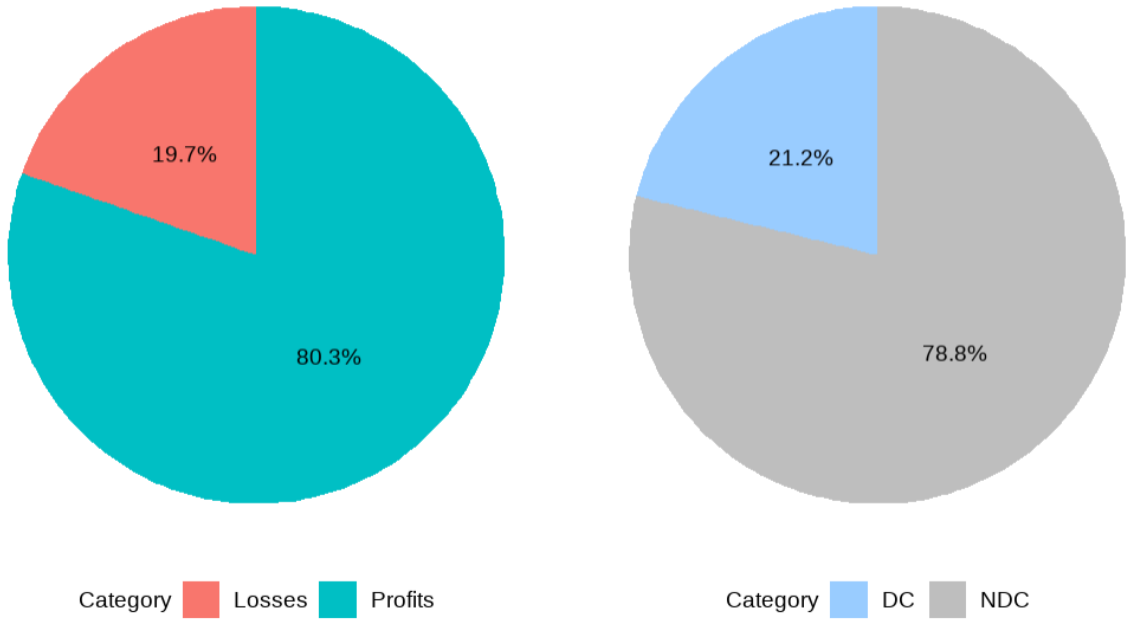
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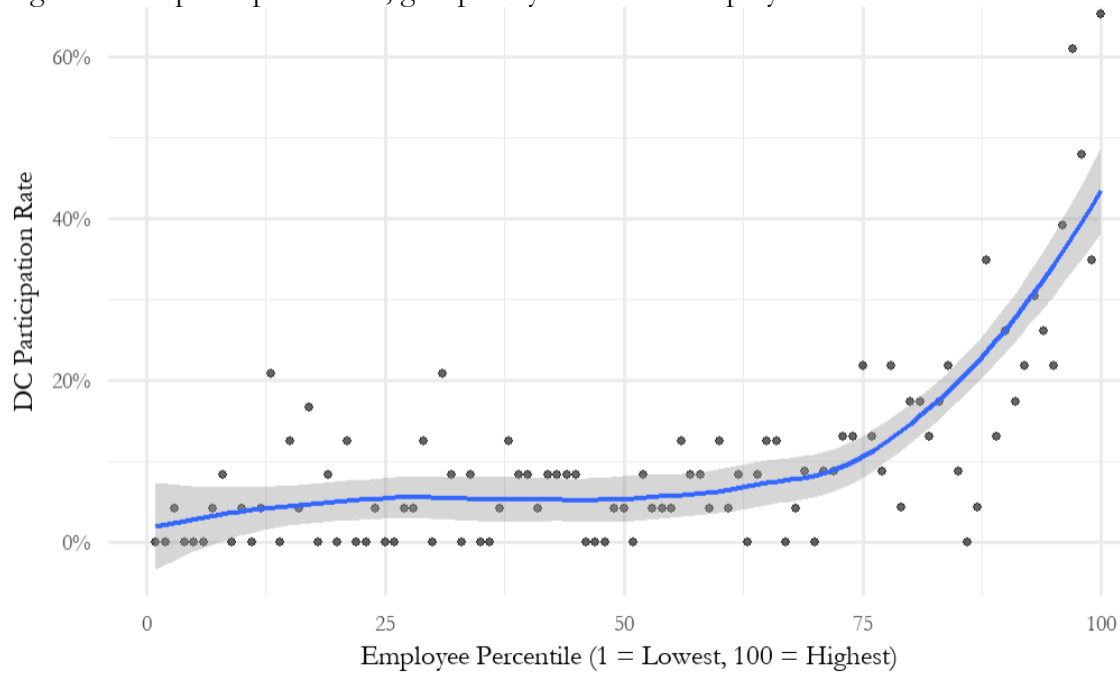
APPENDIX A  
DISTRIBUTION OF LOSSES

Figure 7. Distribution of losses among IT companies and by DC status  
Share of Losses and Profits      Losses by DC Status



APPENDIX B  
DC PARTICIPATION RATE BY EMPLOYEES

Figure 8. DC participation rate, grouped by number of employees in 2021



APPENDIX C

PRELIMINARY DESCRIPTIVE STATISTICS FOR TREATMENT GROUP

Table 8. Preliminary descriptive statistics for DC companies (2020–2024), in thousands UAH

<i>Indicator</i>	<i>Year</i>	<i>Mean</i>	<i>Standard deviation</i>	<i>Min</i>	<i>Max</i>
<b>Total Assets</b>	2020	436	49,980	176,786	0.1
	2021	315	73,375	249,586	19.2
	2022	506	75,936	286,507	0.5
	2023	528	101,842	408,438	0.2
	2024	537	135,663	579,939	1.8
<b>Profit</b>	2020	429	8,791	46,989	-186,887
	2021	313	17,588	103,103	-117,734
	2022	501	16,446	106,074	-308,685
	2023	522	24,057	166,192	-164,633
	2024	535	27,473	142,284	-148,996
<b>Revenue</b>	2020	421	99,464	338,915	10.2
	2021	310	145,668	512,520	0.2
	2022	495	141,291	601,339	3.6
	2023	515	173,037	658,503	0.5
	2024	537	217,878	717,850	73.1

APPENDIX D

PRELIMINARY DESCRIPTIVE STATISTICS FOR CONTROL GROUP

Table 9. Preliminary descriptive statistics for NDC companies (2020–2024), in thousands UAH

<i>Indicator</i>	<i>Year</i>	<i>Mean</i>	<i>Standard deviation</i>	<i>Min</i>	<i>Max</i>
<b>Total Assets</b>	2020	2,601	13,455	128,956	0.1
	2021	2,166	14,655	166,797	0.1
	2022	4,038	14,344	179,391	0.1
	2023	4,259	15,248	188,655	0.1
	2024	4,437	16,409	208,820	0.1
<b>Profit</b>	2020	2,526	1,424	20,416	-61,430
	2021	2,140	1,746	27,654	-178,105
	2022	3,981	1,933	55,850	-185,372
	2023	4,189	2,043	28,511	-110,496
	2024	4,391	1,715	30,654	-182,967
<b>Revenue</b>	2020	2,519	28,089	235,432	0.3
	2021	2,137	33,077	348,738	0.2
	2022	3,955	31,288	465,780	0.1
	2023	4,164	25,701	239,798	-2.2
	2024	4,475	22,761	206,558	0.1

APPENDIX E  
DID MODELING WITHOUT PSM

Table 10. DiD regression models without PSM

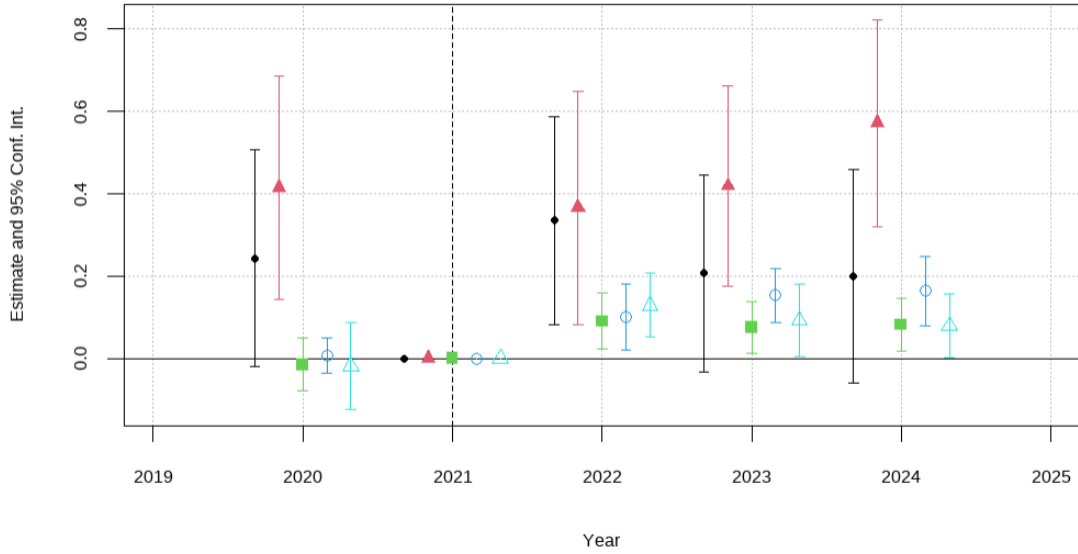
<i>Measures</i>	<i>IHS Profit Margin</i>	<i>IHS ROA</i>	<i>Probability Profit</i>	<i>Log Profit Margin</i>	<i>Log ROA</i>
Intercept	-0.106*** (0.017)	0.004 (0.019)	0.704*** (0.011)	-3.223*** (0.045)	-2.093*** (0.048)
DC	-0.023 (0.049)	0.069 (0.053)	0.068* (0.031)	0.385** (0.121)	0.139 (0.129)
post_period	-0.045** (0.017)	-0.041* (0.018)	-0.054*** (0.011)	0.203*** (0.045)	0.009 (0.048)
DiD estimator	0.037 (0.053)	-0.055 (0.058)	-0.030 (0.034)	-0.038 (0.133)	0.211 (0.142)
log_Employee	0.051*** (0.005)	0.033*** (0.005)	0.039*** (0.003)	-0.052*** (0.013)	-0.050*** (0.014)
Observations	15,493	15,610	15,649	11,152	11,136
R <sup>2</sup>	0.009	0.004	0.018	0.006	0.003

Note: \*\*\* -significance at <1% level, \*\* -significance at 1% level, \* -significance at 5% level

APPENDIX F

TREATMENT EFFECT OF IMPLEMENTING DC

Figure 9. Treatment effect of joining DC on profitability measures



Note: 2021 – pre-treatment basic year, the black spot – Log Profit Margin, the red triangle – Log ROA, the green square – Probability Profit, the empty circle – IHS Profit Margin, the empty triangle – IHS ROA