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PREDICTING THE LEVEL OF FALSIFICATION OF FINANCIAL STATEMENTS IN RUSSIAN MANUFACTURING ENTERPRISES IN 2012–2019

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PREDICTING THE LEVEL OF FALSIFICATION OF FINANCIAL STATEMENTS IN RUSSIAN MANUFACTURING ENTERPRISES IN 2012–2019[2]

This paper considers the falsification of financial reports at Russian manufacturing enterprises in the period from 2012 to 2019. The factors are associated with the heterogeneity of estimates of falsified financial statements. We investigate the evolution of such reporting during the period under review.

Two main lines of behavior of companies in relation to falsified corporate reporting are identified: either a consistently "honest" strategy, which is characteristic of no more than 30–50% of the enterprises, or situational behavior, when an enterprise provides either reliable or questionable data in certain years depending on their circumstances.

For large and medium-sized manufacturing enterprises, the quality of the reporting provided has generally improved in the sanctions period of 2015–2019 compared to the pre-sanction period.

Based on econometric calculations, we demonstrate that the main factors associated with the provision of inaccurate reporting are the size of the enterprise, and the growth rate of accounts receivable in previous years.

JEL Classification: F14, F51, L6, L25.

Keywords: level of reporting falsification, sanctions, crisis, Beneish model, Roxas model, Russian companies

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Introduction

Corporate fraud can lead to significant financial losses, and damage investor confidence and the economy. Several works have been devoted to the study of the causes, motives and consequences of financial distortions and the manipulation of income (DeFond, Jiambalvo, 1994; Ettredge et al., 2010; Hennes et al., 2013, etc.).

Fraud detection is time consuming and challenging. Traditionally, researchers have relied on the analysis of financial data and/or textual content from financial statements to detect corporate fraud. The study of financial fraud began in the 1930s, when Benferd's law was discovered. Benferd's distribution states that for almost any kind of significant data sets (for example, trading volume on stock exchanges) from natural data sources, the first significant digit of each number will be "1" in about 30% of cases; and "2" about 18% of the time. Natural financial accounting data (supply volumes, amounts declared in tax returns, etc.) also obey this distribution even when converting data from one currency to another (Zverev, Nikiforov, 2020). Financial reporting data is also subject to this distribution, so Benferd's distribution began to be used to detect fraudulent corporate reporting.

The main issues discussed in this article are which factors are connected to the heterogeneity of estimates of the falsification of financial statements, what the evolution of corporate fraud in the period under review is and, in particular, whether there a dependence of the report falsification on the sanctions crisis of 2014. The factors influencing the level of report falsification of manufacturing enterprises are checked based on statistical models.

This study contributes to a deeper understanding of financial reporting manipulation by enterprises. In particular, the scale of such manipulations among small, medium, and large businesses was assessed in the pre-sanctions period and in the sanctions period. It is shown that small enterprises are significantly more likely to falsify financial statements than medium and large ones, which may be due to the greater oversight of the latter by state bodies and banks, audits when receiving state support, and the submission of reports in accordance with IFRS.

This article revealed that the presence of report falsification in previous years, the size of the enterprise, the growth rate of accounts receivable, the year the company was founded, and joint-stock company status affect the level of report falsification. From the point of view of the general level of report falsification, during the crisis the level of falsification was higher than in the pre-crisis and post-crisis periods, which may be associated with the adaptation of enterprises.

Literature review

In the 1990s, several works demonstrated methods of manipulating corporate reporting. Carslaw (1988) revealed that New Zealand companies demonstrate manipulation of profits, presumably by rounding up the net profit indicator. Following this work, similar results were shown for US firms (Thomas, 1989). Studies from the 1980s to the 2000s considered the risks of corporate fraud, but without any disaggregation of these risks by the type of fraud (Albrecht et al., 1984; Dzamba, 2004).

Several authors (Beneish, 1999; Dechow et al., 2011) drew attention to the practical importance of building integrated indices that would signal a high risk of fraud in financial reporting. The Beneish model (Beneish, 1999) consists of 8 indicators, which include accounts receivable, revenue, cost of production, assets, current assets, fixed assets, depreciation, net profit, cash flow from operations, long-term and short-term liabilities, and selling and administrative expenses. The essence of the model is that if the growth rate of the index differs from one, then it can be assumed that the company is manipulating their reporting. The decoding of Equation (1) is presented in Appendix 1.

$$M - score = -4{,}84 + DSRI * 0{,}920 + GMI * 0{,}528 + AQI * 0{,}404 + SGI * 0{,}892 + DEPI * 0{,}1158 - SGAI * 0{,}172 + TATA * 4{,}679 - LVGI * 0{,}327 \quad (1)$$

Beneish identified several patterns in report falsification. Young companies are more likely to falsify revenue data. Incorrect accounting of stocks also contributes to the unreliability of reporting. Thus, we can conclude that the process of detecting report falsification is multidimensional.

The indicators in the Dechow model (Dechow et al., 2011) consider changes in: cash sales, the return on assets, working capital, non-current operating funds, receivables, inventory, and the share of intangible assets such as brand awareness or intellectual capital. The main difference between Dechow's model and Beneish's model is that the former includes indicators of intangible assets, reflecting intellectual capital. The decoding of Equation (2) is presented in Appendix 2.

$$PV = -7{,}893 + 0{,}790 * rsst_{acc} + 2{,}518 * ch_{rec} + 1{,}191 * ch_{inv} + 1{,}979 * soft_{assets} + 0{,}171 * ch_{cs} - 0{,}932 * ch_{roa} + 1{,}029 * issue \quad (2)$$

A comparison of the level of forecast accuracy showed the advantages of the Beneish model (89.5%) compared to the Dechow model (63.7%).

In 2011, Roxas modified Beneish's model, considering the specifics of US legal and business practice, removing the indices of net profit, cash flow from operations, long-term and short-term liabilities, and commercial and administrative expenses from the formula (Roxas, 2011), which increased the accuracy of the Roxas model to 87% from 46% for the US corporate sector (the decoding of Equation (3) is presented in Appendix 1):

$$M - score = -6{,}065 + DSRI * 0823 + GMI * 0906 + AQI * 0{,}593 + SGI * 0{,}717 + DEPI * 0{,}107 \quad (3)$$

Wyrobek (2020) carried out a study using machine learning, where financial statements (balance sheet, income statement, cash flow statement and financial ratios) were used as data. In total there were 258 variables and the accuracy was about 95%. As a result, it was found that dishonest companies have high gross margins, but low net income and pay relatively lower taxes compared to honest firms. Dishonest companies were also more active in financial transactions, including obtaining new capital and investing in financial assets. Dishonest companies had relatively lower liquidity ratios, more emergency items and discontinued operations, and higher indebtedness. Kim et al. (2016) considered a model of report falsification, considering intentional and unintentional falsification, which was revealed based on the director's performance and the subjective assessment of colleagues. They found that if the director was respected, then the level of falsification of reporting decreases. Noor & Mansor (2019) analyzed the relationship between the report falsification and the financing of R&D, where information was initially collected for 500 companies, the sample was then reduced to 219 companies. The authors concluded that financing by the company itself, or by other agents, of the company's R&D, the level of report falsification decreases. Dong et al. (2018) assessed the report falsification using financial social networks. They showed the importance of comments on special financial forums from companies in determining the likelihood of report falsification.

Many works assessed the likelihood of report falsification, where they mainly estimated the periods from 1999 to 2015. They built models based on the financial data of companies and used additional non-financial factors—which we check in this work based on Russian data—such as the period of the company, organizational and legal property, the presence of a branch network, the scope of the company, financing in R&D, and company size.

Feruleva and Stefan (2016) adapted the Beneish and Roxas models for Russian companies, considering Russian legislation, and considered the calculation of depreciation charges for Russian companies. The model was tested using a sample of 60 Russian non-listed limited liability and joint-stock companies. The model made it possible to increase the accuracy of determining reportr falsification. When assessing the likelihood of report falsification, the original Beneish model, using Russian data, showed a forecast accuracy of 62%, while the adapted model was 68% accurate. Subsequently, using the same data, Feruleva and Stefan (2017) tested factors affecting the likelihood of report falsification , which included economic, political, scientific, technological and social factors. The main conclusions are that the level of falsified reporting differs depending on the industry and crisis periods in the company’s development. In particular, high inflation provokes companies to file falsified reports. Such factors as military conflicts in the region of the company's activity, the presence of investors from Islamic countries (intolerant of fraud) do not affect the level of falsification.

The following works by Russian authors present the results of theoretical studies to identify the reasons for report falsification. Roschektayev and Roschektaeva (2018) analyzed the increasing the level of report falsification, concluding that elements of internal control affect the level of falsification: the stronger the control, the less opportunities for falsification and, accordingly, the less report falsification. Kogdenko (2015) studied corporate fraud and revealed that the presence of many branches leads to an increase in the likelihood of report falsification, since finances can move between branches. The presence of large accounts receivable increases the likelihood of the manipulation of financial statements, since this may be associated with specifically drawn up contracts, where a long grace period is allowed, or the buyer is not liable to the seller. The main conclusion of Sardarova (2009) is that a sharp change in the dynamics of the share of receivables/payables and a sharp increase in the amount of revenue indicates fraudulent reporting.

In general, there are few empirical studies using data from Russian companies assessing the scale of report falsification compared to studies on other countries, which determines the relevance of this study. Most of the Russian work is limited to the study of the financial performance of a company to detect falsification of statements during audits, overlooking non-financial data.

Methodology and data

This empirical study assesses the level of financial reporting fraud by manufacturing enterprises in Russia from 2012 to 2019. The main questions we address are what factors are connected with the heterogeneity of estimates of financial report falsification, what the evolution of corporate fraud in the period under review is and, in particular, whether there is a dependence of the level of report falsification on the institutional shock associated with the 2014 sanctions crisis.

The work tests several hypotheses that were previously considered in relation to other countries (hypotheses 1, 2, 4, 5, 6, 7, 8) but were not tested on Russian data, as well as original hypotheses (hypotheses 3 and 9).

1. The level of report falsification differs among small, medium and large businesses, that is, the smaller the company, the higher the level of report falsification, since small companies have fewer external monitoring bodies (Beneish, 1999).
2. The level of report falsification differs depending on the age of the enterprise. The younger the company, the higher its level of report falsification, since audits and other inspections by state bodies, do not take place from the moment the company was founded, but after several years, which makes it possible to manipulate financial statements earlier (Beneish, 1999).
3. If the company has falsified financial reports in the past, then it is more likely to falsify them in the future, so that reports look more consistent.
4. If the company has foreign owners, then it will be less inclined to falsify financial statements, since there is additional monitoring in the form of reports being required to follow international standards, not only Russian ones. Foreign-owned companies also care more about their reputation and are less willing to take risks (Firth et al., 2011).
5. The presence of a sharp change in accounts receivable increases the likelihood of report falsification, as this may be associated the misrepresentation of indicators (Sardarova, 2009).
6. A large number of branches increases the likelihood of falsification, since funds can be moved within the structure to inflate or underestimate indicators (Kogdenko, 2015).
7. The higher the level of R&D funding, the lower the likelihood of report falsification, since there is additional monitoring of this segment by government bodies (Noor, Mansor, 2019).
8. Joint-stock companies distort financial statements to a lesser extent, since they have more monitoring bodies in comparison with other types of companies (Chen et al., 2006b).

9. During a crisis, the likelihood of report falsification is higher than in normal times, since during a crisis the economic situation is less stable, there is less monitoring.

The main methodological approach of this study is based on the model outlined in Feruleva and Stefan (2016), where the model and calculation of the value of the border index were adapted for Russian legislation. In this work, the values of the composite index for assessing the risk of report falsification were calculated based on the following parameters:

1. Daily Sales Receivables Index (DSRI)
2. Gross profit margin index (GMI)
3. Asset Quality Index (AQI)
4. Revenue Growth Index (SGI)
5. Depreciation Index (DEPI)
6. Selling and Administrative Expenses Index (SGAI)
7. Dependency Ratio Index (LVGI).

The decoding of the variables is presented in Appendix 1.

The formula for calculating the M-score index is:

$$M - score = -4{,}84 + DSRI * 0{,}920 + GMI * 0{,}528 + AQI * 0{,}404 + SGI * 0{,}892 - SGAI * 0{,}172 - LVGI * 0{,}327 \quad (4)$$

If the M-score is less than -1.802, distortion of financial statements is unlikely, if the M-score is above -1.802 there is a possibility of manipulation. Taking the Russian legislation into account, Stefan and Feruleva (2016) recalculated the threshold value of the composite M-score index of Beneish and Roxas. The Beneish M-score index for Russian companies was -1.802. When using the adjusted boundary values of financial indicators, the quality of forecasts for report falsification by Russian companies becomes more accurate.

The study uses two sources of information:

1. A sample survey of manufacturing enterprises in Russia, the information base of which is data from a survey of enterprises of the project "Factors of Competitiveness and Growth of Russian Industrial Enterprises" carried out in 2018 as part of the HSE

University Program of Fundamental Research. 1,717 enterprises took part in the survey. The sample of enterprises is representative in the context of All-Russian classifier of types of economic activity, size groups of enterprises, and federal districts. During the study, a weighting procedure was used, since the number of large firms in the survey increased compared to their share in the general database. Survey data were supplemented by the author with accounting data for 2012–2019, attached from Ruslan's database. Considering the exclusion of enterprises with no reporting, the final sample contained 1,578 observations.

2. The general set of manufacturing enterprises formed based on data collected by the author from Ruslan's database. The criteria for selecting enterprises are the same as the main parameters of the sample for the observation period 2012–2019. Initially, the sample consisted of 103,906 firms, but after the removal of firms with missing reporting (if at least one indicator was not there in one year, then the company was dropped from the sample), it shrank to 26,172 observations. The array cleaning procedure led to a bias in the sample towards large enterprises. When calculating the bias of the sample through the variance, it was found that the unbiased variance was 0.018, and in the reduced sample it was 0.0017.

Descriptive analysis of the level of falsification of financial statements in 2012–2019

Assessment of the accuracy of financial statements based on the data of the general database of manufacturing enterprises

For all enterprises in the general database, the M-score criterion was calculated, which made it possible to classify firms into two groups—those with a high and low probability of report falsification. Then the average level of report falsification for the pre-sanction period (2012–2014) was calculated, and for the sanctions period (2015–2019) in the aggregate and for small, medium, and large enterprises. The results are presented in Table 1.

Table 1. Average level of falsification of financial statements at manufacturing enterprises in 2012–2019 depending on the size of the enterprise.

Years	For all enterprises		Small enterprises (10-100 emp.)		Average enterprises (101-250 emp.)		Large enterprises (more 250 emp.)	
	mean	N	mean	N	mean	N	mean	N
2012	25,41%	10518	29,92%	7420	23,57%	1349	17,58%	3464
2013	26,79%	14590	30,30%	11447	21,92%	1510	17,45%	3634
2014	29,05%	19594	31,68%	16384	23,64%	1722	19,03%	3851
For the period 2012-2014	**27,09%**	**14900**	**30,63%**	**11750**	**23,04%**	**1527**	**18,02%**	**3649**
2015	29,63%	22914	32,14%	19668	23,39%	1834	18,22%	3963
2016	29,57%	26172	31,88%	22911	20,64%	1967	16,61%	4105
2017	21,26%	14910	24,29%	11645	17,15%	1609	12,67%	3741
2018	22,35%	19067	24,74%	15787	16,94%	1747	13,40%	3896
2019	28,21%	14366	31,28%	11224	23,35%	1867	19,80%	3999
For the period 2015-2019	**26,20%**	**19485**	**28,86%**	**16247**	**20,30%**	**1804**	**16,14%**	**3940**

Source: author's calculations based on RUSLANA data

Table 2 indicates that in 2012–2019 at least a quarter of enterprises have signs of distorted financial statements. In the pre-sanction period 2012–2014, there was an increase in the average level of falsification of reporting and this trend was typical for small, medium, and large enterprises. Leaders in the provision of inaccurate data both in the pre-sanction and sanctions periods are small businesses.

In the sanctions period 2015–2019, there is a slight decrease in the average share of enterprises submitting inaccurate reporting. For the aggregate, the decline was 0.89 percentage points, for small enterprises 1.77 percentage points, for medium-sized enterprises 2.74 percentage points, for large enterprises 2.06 percentage points.

The t-test was used to test the equality of the average levels of reporting falsification in 2012–2014 compared to 2015–2019 (Table 1.2). The hypothesis is not rejected for small companies, however, for all companies, and for medium and large companies, this hypothesis is rejected (the average values for different groups of companies differ significantly), from which it can be concluded that in the sanctions period the quality of financial reporting for all groups of companies, except for small ones, consistently improved through 2018. However, in 2019, there was a jump again in all groups of enterprises, and the average share of enterprises submitting inaccurate reports began to increase again (Table 1 and Fig. 1).

When comparing the data by size groups, for the entire observation period, small companies show the largest share of report falsification (30.63% in 2012–2014 and 28.86% in 2015–2019). The least inclined to distort the reporting are large enterprises (18.02% in 2012–2014 and 16.14% in 2015–2019). Table 1.1 presents the results of the Kruskal-Wallis test, which tested the hypothesis about the equality of the average level of falsification of reporting between small, medium, and large enterprises. It was found that at any level of significance this hypothesis is rejected and the average values for companies of different sizes are not equal in any year of observation between 2012 and 2019.

Table 1.1. Comparison of the average for each year for small, medium, and large enterprises in the general database

Years	Kruskal-Wallis chi-squared	p-value
2012	189.15	***
2013	231.68	***
2014	241.5	***
For the period 2012-2014	2436.6	***
2015	306.38	***
2016	389.38	***
2017	227.54	***
2018	231.01	***
2019	191.63	***
For the period 2015-2019	143.21	***

Source: author's calculations based on RUSLANA data

Next, we assessed whether there were significant changes in the level of report falsification in the period after the introduction of economic sanctions compared to the pre-sanction period (Table 1.2.)

Table 1.2. The average levels of report falsification before and after the introduction of economic sanctions for the pool as a whole and for small, medium, and large enterprises using the t-test.

Years	For all enterprises	Small enterprises	Average enterprises	Large enterprises
2012-2014 2015-2019	0,59095754***	0,6255552	0,42987059**	0,50978348***

Source: author's calculations based on RUSLANA data

The results indicate that the hypothesis of equality of averages in the pre-sanction and sanctions periods is rejected for all companies, and for medium and large enterprises. Only for small businesses were there no significant changes in the scale of inaccurate reporting. Thus, in the sanctions period, there was a significant change for the better on the part of medium and large businesses. This could be because these enterprises attracted state support, which was preceded by a more thorough analysis of their current financial situation.

Fig. 1 shows the levels of report falsification for size groups of enterprises

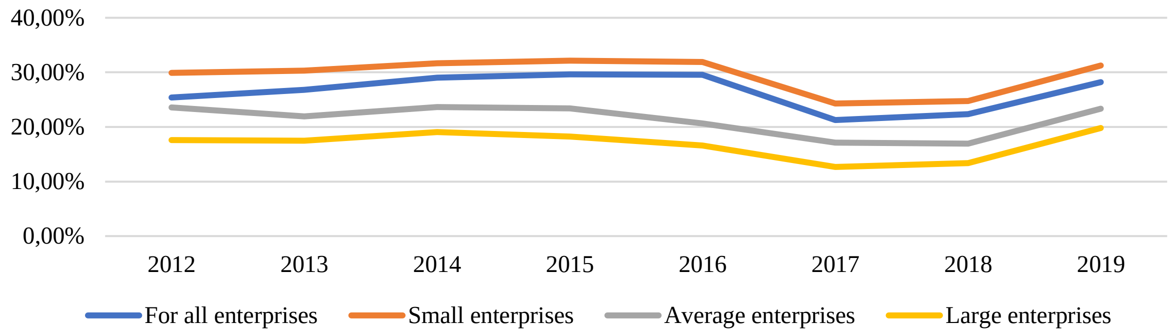

Fig 1. The share of enterprises with unreliable reporting by size groups from 2012 to 2019
Source: author's calculations based on RUSLANA data

Based on the general database, the average level of report falsification was calculated for the period from 2012 to 2019, depending on the age of the company. Three periods were distinguished: "Soviet" companies founded during the period of the planned economy, companies founded during the period from the beginning of market reforms up to the introduction of the economic sanctions, i.e. from 1993 to 2013 and companies founded during the period of the introduction of economic sanctions, i.e. from 2014 to 2019. The results are presented in Table 2.

Table 2. The average level of report falsification at manufacturing enterprises (2012–2019) depending on the age of the enterprise

Years	For all enterprises		Enterprises established before 1992		Enterprises established in 1992-2013		Enterprises established in 2014-2019	
	Mean	N	Mean	N	Mean	N	Mean	N
2012	25,41%	10518	27,50%	8646	15,77%	1871	-	-
2013	26,79%	14590	28,28%	12564	17,58%	2025	-	-
2014	29,05%	19594	30,24%	17376	19,71%	2217	-	-
For the period 2012-2014	**27,09%**	**14900**	**28,68%**	**12862**	**17,69%**	**2037**	**-**	**-**
2015	29,63%	22914	30,86%	20619	34,50%	3452	66,06%	1158
2016	29,57%	26172	30,68%	23839	40,93%	5896	55,78%	3564
2017	21,26%	14910	22,19%	12761	15,74%	2148	-	-
2018	22,35%	19067	23,08%	16749	17,09%	2317	-	-
2019	28,21%	14366	29,33%	12447	31,13%	3916	40,91%	1997
For the period 2015-2019	**26,20%**	**19485**	**29,22%**	**14801**	**27,88%**	**3545**	**54,25%**	**1343**

Source: author's calculations based on RUSLANA data

In general, based on publicly available data, we note that the quality of the reporting provided differs significantly for enterprises of different ages. For enterprises created during the period of market reforms, there was greater volatility from year to year.

Using the Kruskal-Wallis test, the hypothesis of the equality of the average level of report falsification between companies of different ages was tested. It was found that at any level of significance this hypothesis was rejected, and the averages were not equal in any year from 2012 by 2019 (Table 2.1).

Table 2.1. The average for each year for enterprises established in different periods

Years	Bartlett's K-squared	p-value
2012	111.77	***
2013	101.77	***
2014	105.8	***
2015	35.495	***
2016	294.91	***
2017	45.786	***
2018	42.011	***
2019	13.581	***

Source: author's calculations based on RUSLANA data

When comparing the data on age of the company, it was revealed that among the former Soviet companies, the quality of reporting in the periods under review did not change significantly. In the pre-sanction period 28.68% of companies in this group falsified reports and in the sanctions period 29.22% did. Among the companies created during the period of market reforms before the imposition of sanctions there is high volatility in the average share of firms with falsified reporting, and in founded in the sanctions period, the quality of reporting becomes significantly worse, as evidenced by a significant increase in the average share of firms with signs of report falsification (10.19 percentage points).

The t-test was used to test the hypothesis about the equality of the average level of report falsification for the period 2012–2014 compared with the period from 2015–2019 across all enterprises, and by the groups of "Soviet" companies and companies created between 1992 and 2013 (Table 2.2). The hypothesis is not rejected for companies created before 1992, while for the group of enterprises created during market reforms, we observe a significant deterioration in the quality of reporting in the sanctions period compared to the pre-sanction period (the hypothesis of the equality of averages is rejected at a significance level of less 5%). By the sanctions period, the share of enterprises that falsify reports approached the level demonstrated by former Soviet enterprises. Calculations for the group of companies created after 2014 were not made due to the lack of data for them for 2017 and 2018.

Table 2.2. The average levels of report falsification for 2012–2014 and for 2015–2019 for enterprises created in different periods using t-test on the data of the general database

Years	For all enterprises	Enterprises established before 1992	Enterprises established in 1992-2013	Enterprises established in 2014-2019
2012–2014 2015-2019	**0,59095754*** **	0,69779329	**0,17585898** **	-

Years	For all enterprises		Small enterprises		Average enterprises		Large enterprises	
	Mean	N	Mean	N	Mean	N	Mean	N
2012	19,79%	2587	26,06%	1105	22,04%	363	17,45%	1559
2013	17,20%	2587	20,81%	1105	18,18%	363	16,36%	1559
2014	18,32%	2587	22,71%	1105	20,94%	363	16,87%	1559
For the period 2012-2014	**18,44%**	**2587**	**23,20%**	**1105**	**20,39%**	**363**	**16,89%**	**1559**
2015	17,09%	2587	20,00%	1105	19,83%	363	16,74%	1559
2016	15,35%	2587	17,38%	1105	18,46%	363	14,62%	1559
2017	12,56%	2587	16,29%	1105	15,15%	363	10,39%	1559
2018	11,36%	2587	15,20%	1105	12,40%	363	9,04%	1559
2019	17,32%	2587	20,54%	1105	15,43%	363	15,59%	1559
For the period 2015-2019	**14,74%**	**2587**	**17,88%**	**1105**	**16,25%**	**363**	**13,28%**	**1559**

Source: author's calculations based on RUSLANA data

Fig. 2 demonstrates the trends in the level of report falsification depending on the age of the company.

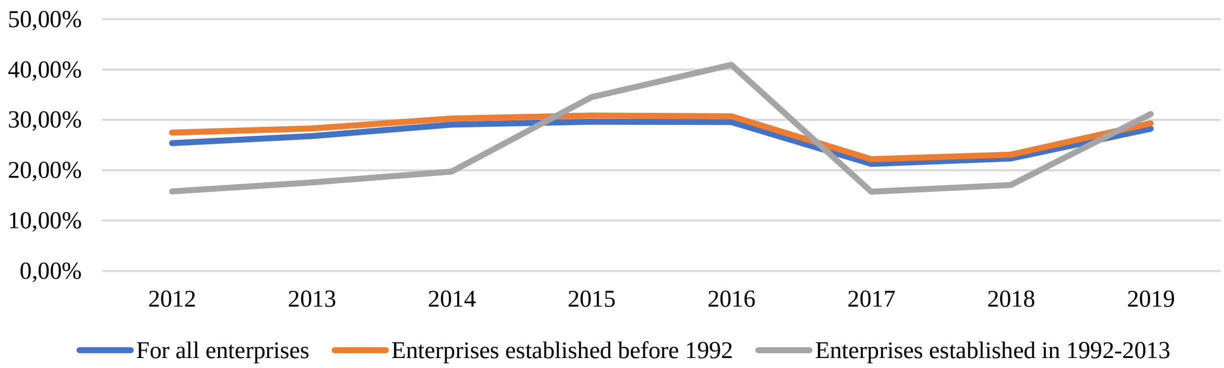

Fig 2. The share of enterprises with inaccurate reporting from 2012 to 2019, depending on their age
Source: author's calculations based on RUSLANA data

Assessment of the quality of financial statements based on panel data

To check the stability of the results of the descriptive analysis at the enterprises from the general database, a panel of 2,587 enterprises annually submitting accounting data was formed. The level of report falsification, depending on the size of enterprises are presented in Table 3.

Table 3. Average level of report falsification at manufacturing enterprises in 2012–2019, depending on the size of the enterprise
Source: author's calculations based on RUSLANA data

For enterprises in the pre-sanction period, inaccurate reporting was typical for 18.44% of the panel's firms, while in the general aggregate they accounted for 27.09%. The sanctions period is characterized by similar results (14.74% of firms with signs of data distortion in the panel and 26.20% in the general pool). This trend is typical for all size of enterprises. In addition, in the panel, gaps in the share of enterprises with unreliable reporting in various sizes of companies are significantly lower than in the general database. This suggests that companies that report regularly are less prone to misrepresenting their performance. The results for small enterprises in the panel are consistent with the results obtained for the general population (see Table 1)—the smaller the enterprise, the higher the level of report falsification.

The t-test was used to test the hypothesis of the equality of the average levels of report falsification in 2012–2014 compared to the period 2015–2019 (Table 3.1). The hypothesis is rejected for all panel data companies at less than 1%. Thus, improved financial reporting is characteristic for all groups of enterprises in the panel.

Table 3.1. The average levels of report falsification for 2012–2014 and for 2015–2019 depending on the size of the enterprise, t-test results

Years	For all enterprises	Small enterprises	Average enterprises	Large enterprises
2012–2014 2015-2019	0,0355***	0,0122***	0,0385***	0,0619***

Source: author's calculations based on RUSLANA data

Fig. 3 demonstrates the tendencies for report falsification, typical for enterprises of various sizes in the panel.

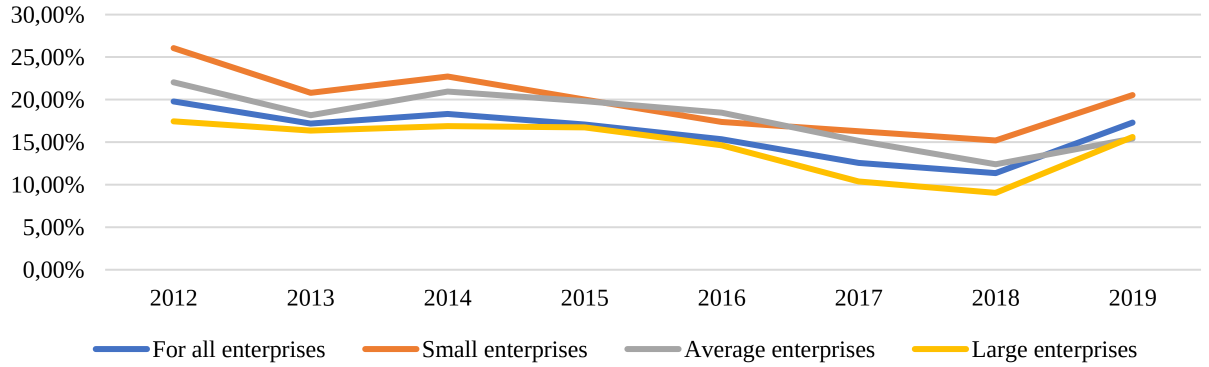

Fig 3. The share of enterprises with unreliable reporting, depending on size from 2012 to 2019
Source: author's calculations based on RUSLANA data

Table 4 shows the results of assessing the percentage of false reports depending on the age of the company based on panel data. For “Soviet” enterprises, the average level of falsification of statements is significantly higher than for companies created in the period 1992–2013; based on the t-test, the hypothesis of equality of means is rejected (Table 4.2).

Table 4. Average level of the falsification of financial statements at manufacturing enterprises in 2012–2019 depending on the age of the enterprise

Years	For all enterprises		Enterprises established before 1992		Enterprises established in 1992-2013		Enterprises established in 2014-2019	
	Mean	N	Mean	N	Mean	N	Mean	N
2012	19,79%	2587	21,92%	1857	14,38%	730	-	-
2013	17,20%	2587	18,69%	1857	13,42%	730	-	-
2014	18,32%	2587	19,28%	1857	15,89%	730	-	-
For the period 2012-2014	**18,44%**	**2587**	**19,96%**	**1857**	**14,57%**	**730**	**-**	**-**
2015	17,09%	2587	18,15%	1857	14,38%	730	-	-
2016	15,35%	2587	15,83%	1857	14,11%	730	-	-
2017	12,56%	2587	13,8%	1857	9,18%	730	-	-
2018	11,36%	2587	12,44%	1857	8,63%	730	-	-
2019	17,32%	2587	18,09%	1857	15,34%	730	-	-
For the period 2015-2019	**14,74%**	**2587**	**19,51%**	**1857**	**12,33%**	**730**	**-**	**-**

Source: author's calculations based on RUSLANA data

Table 4.1. Average levels of reporting fraud in 2012–2019 for each year for enterprises established in different periods

Years	Bartlett's K-squared	p-value
2012	18.731	***
2013	10.183	***
2014	4.0184	
2015	5.2396	*
2016	1.1964	
2017	10.604	***
2018	7.5471	**
2019	2.7696	

Source: author's calculations based on RUSLANA data

Table 4.2. Average levels of report falsification for 2012–2014 and for 2015–2019 by enterprises created in different periods, t-test

Years	For all enterprises	Enterprises established before 1992	Enterprises established in 1992-2013	Enterprises established in 2014-2019
2012–2014 2015-2019	0,03550165*	0,02151947	0,1485914*	-

Source: author's calculations based on RUSLANA data

Fig. 4 shows the trends in the level of falsification of reports depending on the age of the company.

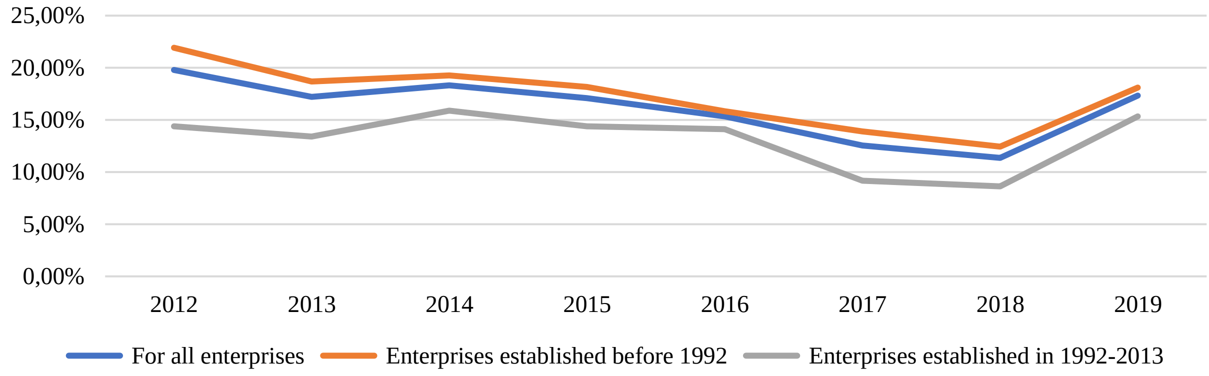

Fig 4. The share of enterprises with report falsification in 2012–2019 depending on the age of the enterprise, %
Source: author's calculations based on RUSLANA data

Table 5 presents the summary results of the level of report falsification for the general database, for the panel, and according to the data of a sample survey for small, medium, and large enterprises from 2012 to 2019, to check the stability of the results from different samples.

Table 6 presents the results of the t-test for the general database, for the panel, and according to the sample survey data for from 2012 to 2019 to check the stability of the results obtained on different samples.

The results indicate that the data on the level of report falsification in the general database and in the survey differ significantly for all enterprises and for each size of company. For all enterprises participating in the survey, accounting indicators are more likely to be reliable than indicators for the entire general database. The discrepancies are mainly due to the group of small enterprises. This bias may be since relatively more “honest” small businesses are included in the panel and in the survey. Perhaps this is because “dishonest” firms that have something to hide are more likely to refuse to participate in surveys.

For medium and large enterprises in the general database, the quality of the reporting improved slightly in the sanctions period of 2015–2019 compared to pre-sanction period. For the enterprises in the panel, the improvement is fixed for all groups of enterprises. The discrepancy between the general database and the panel for small businesses may be due to the greater inclination of relatively more transparent small businesses to participate in surveys.

Table 5. Levels of report falsification in 2012–2019 according to the population, sample survey, and panel depending on the size of enterprises

Years	For all enterprises			Small enterprises			Average enterprises			Large enterprises		
	General	cluster sampling	Panel	General	cluster sampling	Panel	General	cluster sampling	Panel	General	cluster sampling	Panel
2012	25,41%	20,35%	19,79%	29,92%	15,91%	26,06%	23,57%	12,50%	22,04%	17,58%	20,92%	17,45%
2013	26,79%	16,37%	17,20%	30,30%	18,18%	20,81%	21,92%	18,75%	18,18%	17,45%	16,33%	16,36%
2014	29,05%	19,91%	18,32%	31,68%	27,27%	22,71%	23,64%	35,42%	20,94%	19,03%	18,37%	16,87%
For the period 2012-2014	**27,09%**	**18,88%**	**18,44%**	**30,63%**	**20,45%**	**23,20%**	**23,04%**	**22,22%**	**20,39%**	**18,02%**	**18,54%**	**16,89%**
2015	29,63%	22,12%	17,09%	32,14%	22,73%	20,00%	23,39%	18,75%	19,83%	18,22%	22,96%	16,74%
2016	29,57%	22,12%	15,35%	31,88%	18,18%	17,38%	20,64%	16,67%	18,46%	16,61%	23,47%	14,62%
2017	21,26%	21,68%	12,56%	24,29%	40,91%	16,29%	17,15%	29,17%	15,15%	12,67%	19,90%	10,39%
2018	22,35%	12,83%	11,36%	24,74%	13,64%	15,20%	16,94%	18,75%	12,40%	13,40%	13,27%	9,04%
2019	28,21%	20,80%	17,32%	31,28%	25,00%	20,54%	23,35%	22,92%	15,43%	19,80%	21,94%	15,59%
For the period 2015-2019	**26,20%**	**19,91%**	**14,74%**	**28,86%**	**24,09%**	**17,88%**	**20,30%**	**21,25%**	**16,25%**	**16,14%**	**20,31%**	**13,28%**

Source: author's calculations based on RUSLANA data

Table 6. Results of the t-test for the sample survey, general population, and panel data for manufacturing enterprises in 2012–2019 depending on the size of the enterprise

Years	For all enterprises			Small enterprises			Average enterprises			Large enterprises		
	General + cluster sampling	cluster sampling+ Panel	Panel+ General	General + cluster sampling	cluster sampling+ Panel	Panel+ General	General + cluster sampling	cluster sampling+ Panel	Panel+ General	General + cluster sampling	cluster sampling+ Panel	Panel+ General
2012	0,1061***	0,4389	0,0813**	0,0230***	0,1693*	0,1270***	0,1612***	0,2690*	0,1264**	0,3530*	0,2527	0,2122**
2013	0,0208***	0,4031	0,0178*	0,1389***	0,4165	0,0090*	0,3337***	0,2374	0,0510	0,0805*	0,2563	0,1012*
2014	0,0170***	0,1640	0,0340**	0,1199***	0,4227	0,0298***	0,2721**	0,2100*	0,0030	0,4624**	0,0151	0,0966
For the period 2012-2014	**0,0142*****	0,2222	0,0578*	**0,0125*****	0,4988	0,0752*	**0,1943****	0,4197	0,0463	**0,2152***	0,1674	0,0424**
2015	0,0013***	0,0466	0,0200	0,0584***	0,1592	0,0281*	0,0247***	0,0771	0,0751	0,0575**	0,0550*	0,0465*
2016	0,2679***	0,0467*	0,0752*	0,4694***	0,2396	0,0895	0,3515***	0,2904	0,0137	0,0084**	0,0114*	0,0216
2017	0,2640***	0,1991*	0,0369**	0,4374***	0,2701*	0,0279***	0,2024**	0,1146	0,1179	0,2557*	0,1168*	0,0966
2018	0,0395***	0,1227	0,0015	0,0861***	0,3571	0,0188***	0,3242***	0,0261*	0,0843	0,2693*	0,0629	0,0056
2019	0,0260***	0,0614	0,0081	0,0432***	0,0517	0,0035***	0,3853***	0,0626*	0,0995	0,0991*	0,0161	0,0601
For the period 2015-2019	**0,2700*****	0,2335	0,2500*	**0,2348*****	0,2697	0,2500***	**0,2470*****	0,2340	0,2500	**0,2633****	0,2723	0,2500

Source: author's calculations based on RUSLANA data

The evolution of company strategies for filing financial statements

Further results are based on panel data and sample survey data, despite all the limitations mentioned earlier (research on more "honest" enterprises). Table 8 provides information on company reporting behavior on panel and survey data up to 2014 and from 2015 to 2019.

Table 7. T level of report falsification before and after the introduction of sanctions

	Panel data, N	Panel data,%	Survey data, N	Survey data,%
Submitted dishonest reports up to 2014 for all years of the period and continue to do so in 2015-2019.	324,00	12,52%	12,00	0,76%
Submitted honest reports until 2014 for all years of the period and submit honest reports in 2015-2019 for all years of the period	927,00	35,82%	976,00	61,86%
Filed dishonest until 2014 for all years of the period, but then corrected - they serve honest for all years	14,00	0,54%	0,00	0
Filed honest reports before 2014 for all years of the period, but began to distort after (for all years of the period)	0,00	0	0,00	0
And in 2012-2014, and in 2015-2019. in some years they serve either honest or dishonest information	1323,00	51,12%	590,00	37,38%
Total	2587	100,0	1578	100,0

Source: author's calculations based on RUSLANA data

Figure 5 shows the strategies of company behavior in terms of filing reports for the two periods under consideration for the enterprises in the panel, where half of the companies (51.12% do not adhere to a certain strategy (falsifying then submit correct reports), a third of companies (36%) in both periods provided correct reporting, and 12% falsified and continued to file false reports. An insignificant number of companies—only 14 (0.54%)—changed their strategy and stopped falsifying reports after 2014, i.e. this strategy is not typical There were no cases of a change in strategy in the opposite direction—the transition from honest reporting in the pre-sanction period to a dishonest reporting in the sanctions period.

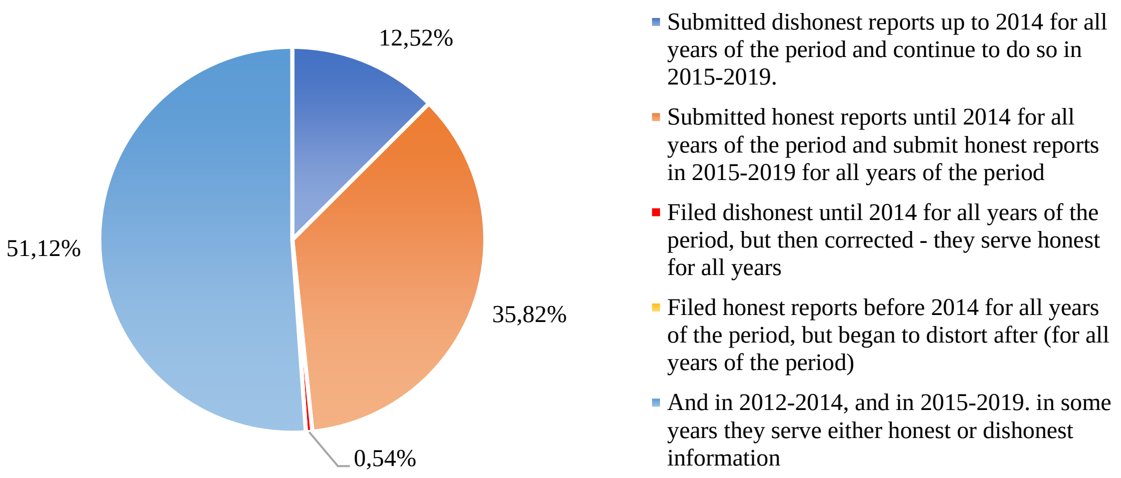

Fig 5. Dynamics of the level of falsification of reports in the pre-sanction (2012-2014) and sanctions periods (2015-2019) according to panel data,%
Source: author's calculations

Figure 6 shows the dynamics of company behavior in falsifying reports based on sample survey data. The results are only partially consistent with the panel data, and only for companies whose position in terms of reporting changes from year to year. The panel has a significantly higher share of companies submitting honest reports for both observation periods.

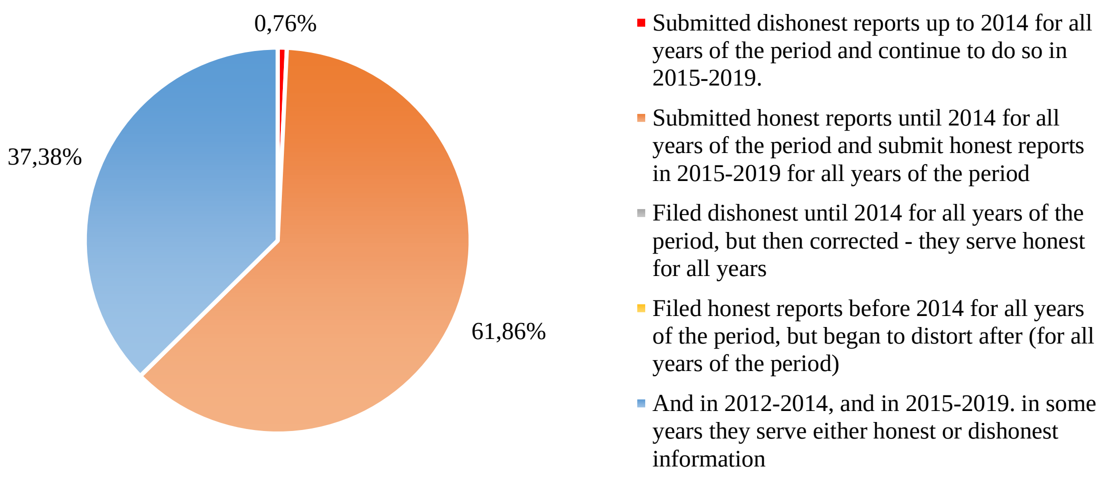

Fig. 6. Dynamics of the level of falsification of reporting pre-sanction (2012-2014) and sanctions periods (2015-2019) according to the sample survey,%
Source: author's calculations

As follows from Table 8, in general, there are two lines of behavior of companies in relation to the filing of corporate reporting: either a consistently honest strategy, which is characteristic of a third of the enterprises in the panel and half of the enterprises in the survey, or situational behavior that changes in a particular year, depending on the circumstances. These estimates are the upper bound of the share of enterprises that represent real results, but the situation is most likely worse.

Results of econometric analysis of factors related to the submission of inaccurate financial statements

For further analysis, a probit model is used, which makes it possible to assess the dependence of qualitative (binary) variables on a variety of factors. This model is based on panel data from the general database. As a dependent variable, the estimate of report falsification for 2018 is used "1" if there are signs of reporting falsification in 2018, "0" otherwise.

As explanatory variables, we use the logarithm of the number of employees in 2018, or a categorical variable, where the basic category is large enterprises, the growth rate of accounts receivable for 2017–2018, the presence of foreign ownership, which takes a binary form, "1" if there is foreign ownership in the company, "0" otherwise; the fact of report falsification for previous periods, "1" if the company falsified reporting in 2017 and in 2016,[3] 0 otherwise; organizational and legal form of the enterprise (binary variable, "1" if a joint-stock company, 0 othewise; binary variable of a branch, "1" the presence of branches, 0 otherwise; age of the company, calculated as "2018 minus the year of establishment of the enterprise".

The hypothesis that there is a positive relationship between the funding of R&D and the quality of reporting is tested only based on the sample survey, since for the general database, information on R&D funding is not available in the RUSLANA database.

The hypothesis that a company has a branch defaults to company size, since the sample of small and medium-sized firms includes only companies that do not have branches, and the sample of large ones does not include companies that do not have branches.

We use as control variables the type of economic activity (categorical variable where food processing is used as the base category). The model is calculated for the sample and for large, medium, and small enterprises (Table 8).

[3] It was revealed that companies which falsified data in 2017 and in 2016 did not falsify data in 2015, but before that several companies falsified data, therefore only two periods were included in the calculation of the indicator.

Table 8. The relationship between estimates of falsification of reporting in 2018 using the probit model

	Model 1	Model 2	Model 3	Model 4	Model 5
Variables	For all enterprises	For all enterprises	Small enterprises	Average enterprises	Large enterprises
Employed, log	**-0.544*** **		**-0.594*** **	**-11.771***	**-0.648*** **
	(0.081)		(0.161)	(6.523)	(0.136)
Small enterprises		**0.379*** **			
		(0.095)			
Average enterprises		0.057			
		(0.120)			
Accounts receivable growth rate 2018–2017.	**1.299*** **	**1.267*** **	**1.217*** **	**3.048*** **	1.327***
	(0.073)	(0.072)	(0.102)	(1.049)	(0.101)
Falsification of reporting (2017,2016)	0.318	0.332	0.268	-7.625	**0.650** **
	(0.223)	(0.225)	(0.304)	(1,649.494)	(0.306)
Foreign ownership	0.006	-0.027	0.167	-1.730	-0.034
	(0.104)	(0.103)	(0.153)	(1.601)	(0.139)
Joint-stock company	**0.202** **	**-0.146***	**0.258***	1.778	- 0.166
	(0.096)	(0.095)	(0.143)	(1.137)	(0.130)
Date of establishment of the company	0.00005	-0.00000	-0.0001	-0.0001	0.0001
	(0.0001)	(0.0001)	(0.0002)	(0.001)	(0.0001)
Controlled by a two-digit OKVED code	Yes	Yes	Yes	Yes	Yes
Constant	**-2.066*** **	**-3.407*** **	**-1.721*** **	**18.618**	**-1.918*** **
	(0.222)	(0.164)	(0.359)	(12.436)	(0.380)
Observations	2,478	2,478	994	142	1,342
Log Likelihood	-521.443	-537.334	-249.472	-11.701	-276.096
Akaike Inf. Crit.	1,094.886	1,128.667	550.944	71.403	604.191

*** p <0.001; ** p <0.01; * p <0.05; p <0.1.
Source: author's calculations

The analysis showed that if an enterprise falsified statements over the past two years, then the likelihood of falsifying statements in the next period significantly increases for large enterprises. The higher the growth rate of accounts receivable in 2017–2018 in the sample as a whole and in all size groups of enterprises, the higher the likelihood that the company falsified reports. The hypothesis about the heterogeneity of estimates was confirmed, since the larger the enterprise, the less often it falsifies reports. Medium-sized firms demonstrate approximately the same level of falsification as large ones, but small firms are significantly more likely to falsify statements. If the company is a joint-stock company, then the likelihood of falsification of reporting is lower for the sample as a whole and for large enterprises, which may be associated with closer monitoring of large taxpayers by the state, and the fact that such companies submit annual reports on activities on an ongoing basis. Companies that are listed on the stock exchange are more closely monitored, which makes it impossible to falsify reports. Only for large companies was a positive and significant result was, indicating the consistency of the chosen strategy of behavior in terms of filing reporting, namely, if the company falsified reporting in the previous period, then the probability that it will falsify it in the future is significantly higher. The influence of the age of the company on the quality of the submitted reports was not found in this model.

Since the threshold value of the probability of reporting falsification is -1.802 and the frequency analysis revealed that there are several companies for which the indicator deviates slightly from this value, it makes sense to form groups with a low, medium, and high probability of report falsification for the multidimensional probit model, which checks the stability of the results (Table 9).

Table 9. Criteria for assigning enterprises to groups with a low, medium, and high probability of reporting falsification based on the values of the M-score index

Index value	Low probability falsification	Average probability falsification	High probability falsification
M-score	<-1,802	-1.802 to -1	>-1

Source: author's calculations

The estimate of falsification of financial statements for 2018 is used as a dependent variable in the multinomial model. Table 10 shows the results, where the base category for comparison is enterprises with an average probability of financial report falsification.

Table 10The relationship between estimates of falsified reporting in 2018 using the mprobit model

	Model 1		Model 2		Model 3		Model 4	
	For all enterprises		Small enterprises		Average enterprises		Large enterprises	
Variables	High probability of falsification	Low probability of falsification	High probability of falsification	Low probability of falsification	High probability of falsification	Low probability of falsification	High probability of falsificatio n	Low probability of falsification
Employed, log	**-0.521***	**0.843*****	0.136	**0.743*****	3.696	4.004	-0.107	**0.603****
	(0.306)	(0.159)	(0.502)	(0.279)	(7.772)	(3.199)	(0.688)	(0.289)
Accounts receivable growth rate 2018–2017.	**0.304*****	**-2.406*****	0.114	**-1.133*****	-2.194	**-1.749***	**-2.276****	**-1.337*****
	(0.078)	(0.147)	(0.202)	(0.199)	(4.065)	(0.926)	(1.156)	(0.326)
Falsification of reporting (2017,2016)	0.684	-0.440	-0.181	0.232	1.627	16.629	1.412	-0.830
	(0.618)	(0.454)	(1.163)	(0.606)	(8,019.282)	(5,628.440)	(0.947)	(0.537)
Foreign ownership	-0.638	**-0.092***	**-1.004***	**-0.453***	-13.930	0.946	-0.578	0.297
	(0.449)	(0.210)	(0.553)	(0.261)	(2,883.174)	(1.110)	(0.806)	(0.281)
Joint-stock company	0.181	**-0.369***	0.603	-0.347	21.556	-1.197	0.361	-0.343
	(0.356)	(0.195)	(0.487)	(0.295)	(34.363)	(0.893)	(0.571)	(0.264)

Date of establishment of the company	-0.0002	-0.0001	**-0.002***	0.00002	-1.928	0.0003	-0.0002	-0.0002
	(0.0003)	(0.0001)	(0.004)	(0.0004)	(2.867)	(0.001)	(0.0003)	(0.0001)
Controlled by a two-digit OKVED code	Yes		Yes		Yes		Yes	
Constant	-0.958	4.049***	-1.323	1.996***	-7.373	-4.555	1.168	2.612***
	(0.646)	(0.392)	(1.137)	(0.639)	(16.405)	(6.731)	(2.100)	(0.877)
Observations	2478		994		142		1342	
R2	0.340		0.372		0.448		0.360	
Log Likelihood	-655.216		-313.241		-28.426		-333.683	
LR Test	676.262*** (df = 14)		370.317*** (df = 52)		46.073*** (df = 14)		375.801*** (df = 14)	

*** p <0.001; ** p <0.01; * p <0.05; p <0.1.
Source: author's calculations

The multinomial model, in general, demonstrates similar results: significant variables affecting the likelihood of falsification of financial statements are the size of the enterprise (number of employees) and the growth rate of accounts receivable, but there are some differences. For example, the presence of foreign ownership is significant for all enterprises and for small businesses. The negative sign for the coefficient of foreign ownership indicates that these enterprises are significantly less likely to submit inaccurate reporting.

In general, empirical testing of the hypotheses put forward has shown the following. The first hypothesis is fully confirmed: the larger the company, the less likely it is to falsify reoprts. The third hypothesis is also fully confirmed: the higher the growth of accounts receivable, the higher the likelihood that the company will falsify reports. The fourth hypothesis is not confirmed, with conflicting results for small businesses that need additional testing. The hypothesis of the relationship between the age of an enterprise and the quality of reporting is partially confirmed, since the indicator of age was significant only for small enterprises at the 10% level and, most likely, this result is unstable. The hypothesis about the influence of the presence of branches on the quality of reporting could not be verified due to the specifics of the data.

Another check of the results for stability was carried out without dividing companies into groups according to falsifiability, using the numerical value of the M-score indicator as a dependent variable. Recall, the higher this indicator, the higher the likelihood that the company falsifies reports. For further analysis, a regression model will be used, where the M-score, calculated based on the Beneish model is a dependent variable; the results are presented in Table 11.

Table 11. The relationship of estimates of falsification of reporting in 2018 using a regression model

	Model 1	Model 2	Model 3	Model 4
Variables	For all enterprises	Small enterprises	Average enterprises	Large enterprises
Employed, log	**-2.544***	-2.933	**-2.217****	**-0.055***
	(1.868)	(6.103)	(0.904)	(0.033)
Accounts receivable growth rate 2018–2017.	0.118	0.123	**1.052*****	**0.772*****
	(0.690)	(1.189)	(0.168)	(0.014)
Falsification of reporting (2017,2016)	**65.390*****	**132.888*****	0.470	0.077
	(6.028)	(13.562)	(0.445)	(0.089)
Foreign ownership	-1.558	-4.106	-0.145	**-0.066****
	(2.490)	(6.402)	(0.258)	(0.033)
Joint-stock company	-2.187	-6.240	**0.493****	**-0.059***
	(2.274)	(6.012)	(0.207)	(0.031)
Date of establishment of the company	0.0002	-0.001	**-0.0003***	**0.00003***
	(0.002)	(0.007)	(0.0002)	(0.00002)
Controlled by a two-digit OKVED code	Yes	Yes	Yes	Yes
Constant	11.628**	**29.128****	1.002	-3.434***
	(5.045)	(14.106)	(2.001)	(0.093)
Observations	2478	994	142	1342
R2	0.018	0.038	0.227	0.393
Adjusted R2	0.015	0.030	0.183	0.390
Residual Std. Error	86.912 (df = 7393)	135.976 (df = 2956)	1.738 (df = 402)	0.947 (df = 4591)
F Statistic	5.488*** (df = 25; 7393)	4.692*** (df = 25; 2956)	5.131*** (df = 23; 402)	119.016*** (df = 25; 4591)

*** p <0.001; ** p <0.01; * p <0.05; p <0.1.
Source: author's calculations

Based on the analysis of the results presented in Table 11, we can conclude that the smaller the company, the higher the level of falsification of reporting. For growth in accounts receivable, the probability of falsification is significantly higher only for medium and large enterprises. Report falsification in previous years is significantly correlated with falsification in the subsequent period for the sample as a whole and for small enterprises. For the age of the company, the results are opposite for medium and large companies, but we do not comment on them, since they are statistically insignificant. In addition, the sample of medium-sized companies is small, which increases the risk of results bias.

Hypotheses were not tested on the sample survey data, since only 393 enterprises were included in the sample, for which it was possible to calculate report falsification based on RUSLANA data. Sample depletion will result in biased results.

Conclusions

This paper assessed the level of falsification of financial statements in the period from 2012 to 2019 and determined what caused the heterogeneity of estimates of the falsification of financial statements. It was revealed that the presence of falsification in previous years, the size of the enterprise, the growth rate of accounts receivable, the age of the company, and the legal form of the company is interrelated with the quality of reporting, therefore, to improve the accuracy of the model, these indicators must be considered. From the point of view of the general level of report falsification, during the crisis (from 2014–2016) the level of falsification was higher than in the pre-crisis and post-crisis periods, which may be associated with a period of adaptation for enterprises.

This study makes an additional contribution to the literature on the distortion of financial statements by Russian enterprises. Using large data sets, in contrast to previous studies, we were able to identify the factors in the quality of reporting in manufacturing enterprises. In the period from 2012 to 2014, a large proportion of companies falsified reports in comparison with the sanctions period from 2015 to 2019.

It was possible to confirm the results of foreign studies in terms of the impact of company size, ownership, and growth in accounts receivable on the likelihood of falsification of financial statements. It was not possible to calculate the hypothesis on the influence of filiality or R&D funding on report falsification, due to limited data.

It was revealed that companies have two typical strategies, that is, if a company falsified data in 2012–2014, then it continued to falsify in 2015–2019. If the company submits correct reporting in the period from 2012 to 2014, then it is more likely to submit accurate reports in the sanctions period.

There are some limitations in this work, to which a limited set of data can be attributed, since the data is analyzed for a short period of time, therefore, the results on different time intervals may differ. In the future it will be necessary to expand the time period to check the robustness of the results. A limited set of factors was tested, therefore, additional effects on the level of reporting falsification cannot be taken into account. The sample for the general population is not representative of size groups.

The results also have important methodological significance clearly indicating that to check the robustness of the results of empirical works that use survey data with attached accounting reports and to obtain reliable conclusions, it is necessary to consider the likelihood that the reports may be unreliable. This will require additional adjustments to calculations based on this indicator.

It should also be borne in mind that survey data are biased towards enterprises which report more correctly.

The results of the study are preliminary and present a general picture of the level of falsification of financial statements in the manufacturing industry. Further areas of research will be related to the identification and analysis of additional factors that may affect the level of report falsification and change the strategies of company behavior in terms of the quality of corporate reporting in different periods, including during the period of a sharp change in the institutional conditions in the Russian economy, associated with the introduction of economic sanctions.

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Appendix 1

Daily Sales Index in Accounts Receivable (DSRI):

$$\frac{\text{Accounts receivable of the current year}}{\text{Revenue of the current year}} * \frac{\text{Revenue of the previous year}}{\text{Accounts receivable from the previous year}}$$

Gross profit margin index (GMI):

$$\frac{\text{Last year's revenue} - \text{Cost of last year}}{\text{Revenue of the current year} - \text{Cost of the current year}} * \frac{\text{Last year's revenue}}{\text{Revenue of the current year}}.$$

Asset Quality Index (AQI):

$$\frac{(\text{Assets} - \text{Current assets} - \text{Fixed assets}) \text{ of the current year}}{(\text{Assets} - \text{Current assets} - \text{Fixed assets}) \text{ last year}} * \frac{\text{Last year's assets}}{\text{Assets of the current year}}.$$

Revenue Growth Index (SGI):

$$\frac{\text{Revenue of the current year}}{\text{Revenue of the previous year}}.$$

Depreciation Index (DEPI):

$$\frac{\text{Depreciation last year}}{\text{Depreciation of the current year}} * \frac{(\text{Depreciation} + \text{Fixed assets}) \text{ of the current year}}{(\text{Depreciation} + \text{Fixed assets}) \text{ last year}}$$

Selling and Administrative Expenses Index (SGAI):

$$\frac{\text{Selling and administrative expenses of the current year}}{\text{Selling and administrative expenses last year}} * \frac{\text{Last year's revenue}}{\text{Revenue of the previous year}}.$$

Dependency Ratio Index (LVGI):

$$\frac{\text{Short} - \text{term and long} - \text{term liabilities of the current year}}{\text{Short} - \text{term and long} - \text{term liabilities of the previous year}} * \frac{\text{Last year's assets}}{\text{Assets of the current year}}.$$

Total Accruals to Total Assets (TATA):

$$\frac{\Delta\text{Net current assets} - \Delta\text{Cash}}{\text{Current year assets}} + \frac{\Delta\text{Corporate Income Tax} - \text{Depreciation}}{\text{Current year assets}} + \frac{\Delta\text{Current part of long} - \text{term liabilities}}{\text{Current year assets}}$$

Appendix 2

RSST accruals:

$$rsst_{acc} = \frac{\Delta\text{WC} + \Delta\text{NCO} + \Delta\text{FIN}}{\text{Average total assets}}, \ where$$

WC = [Current Assets – Cash and Short-term Investments] –[Current Liabilities – Debt in Current Liabilities];

NCO = [Total Assets –Current Assets) Investments and Advances] – [Total Liabilities – Current Liabilities– Long-term Debt];

FIN = [Short-term Investments + Long-term Investments] – [Long-term Debt + Debt in Current Liabilities + Preferred Stock]

Change in receivables:

$$ch_{rec} = \frac{\Delta \text{Accounts Receivable}}{\text{Average total assets}}$$

Change in inventory:

$$ch_{inv} = \frac{\Delta \text{ Inventory}}{\text{Average total assets}}$$

% Soft assets:

$$soft_{assets} = \frac{\text{Total Assets} - \text{PP\&E} - \text{Cash and Cash Equivalent}}{\text{Total Assets}}$$

Change in cash sales:

$$ch_{cs} = \text{ Percentage change in cash sales (Sale)} - \Delta \text{Accounts Receivable}$$

Change in return on assets:

$$ch_{roa} = \frac{\text{Earnings}_t}{\text{Average total assets}_t} - \frac{\text{Earnings}_{t-1}}{\text{Average total assets}_{t-1}}$$

Actual issuance (*issue*) – an indicator variable coded 1 if the firm issued securities during year (t)

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