Identifying Sanction Busters: An Application of Anomaly Detection Algorithms

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Abstract: Sanction evasion undermines the effectiveness of economic sanctions. This study applies unsupervised anomaly detection algorithms to firm-level financial data to identify companies potentially engaged in sanction evasion. Based on economic reasoning, hypotheses are developed on how sanction-busting activities might manifest in financial statements. Using firm data from the Orbis database, three detection techniques (univariate outlier detection, Mahalanobis distance, and Local Outlier Factor) are employed to flag anomalous firms, and a RIPPER rule-based classifier further categorizes detected anomalies based on financial characteristics. The results show that unsupervised anomaly detection effectively identifies firms warranting further investigation, with three out of eight web-searched firms exhibiting economic ties to Russia post-2022. These findings demonstrate that financial anomalies can serve as an indicator of suspicious business activity, warranting closer scrutiny by regulators.

Keywords: Sanction Evasion, Anomaly Detection, Financial Forensics

JEL-Codes: F23, F51, K42

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1. Introduction

Since the invasion of Ukraine in February 2022, an unprecedented wave of sanctions has been imposed on Russia by Western nations and their allies. These sanctions aim to isolate Russia from the global economy by limiting its access to financial markets, advanced technologies, and suppress revenues from exports of oil and gas.[1] However, as the war continues, concerns have been raised regarding the overall effectiveness of these sanctions (Norman and Kantchev 2024). While they have succeeded in slowing down the Russian economy, their effect has been somewhat underwhelming. Several factors contribute to the diminished efficiency of sanctions, one of which is Russia's ability to circumvent restrictions through a practice known as sanction busting (Edward 2024).

Sanction busting refers to the various methods and strategies employed by individuals, companies, and even states to evade or undermine international sanctions (Early 2009, 2011). This can take the form of illicit trade, using intermediaries or third-party countries to channel restricted goods or services, or exploiting loopholes in existing legislation. In the case of Russia, this entails rerouting consumer goods through neighboring countries and sourcing technical components from geopolitical allies like Belarus or China (Gavin and Aarup 2023; Yatskova 2025). Such activities pose a significant challenge to the enforcement of sanctions and thus the effectiveness of these measures.

Recent research highlights the extent of sanction-busting activities and their implications. Chupilkin et al. (2024) show that intermediated trade through neutral countries such as Turkey, the United Arab Emirates (UAE), and China has offset about one-third of the reduction in direct exports from sanctioning economies, particularly for industrial-capacity goods and dual-use technologies. Similarly, Moldashev (2023) highlights a significant rise in Kazakhstan's exports of machinery, vehicles, and electrical equipment to Russia, suggesting re-exports of sanctioned goods. Issabayev and Moldashev (2024) find that both EU and Eurasian Economic Union (EAEU) countries are more prone to sanction-busting than non-aligned countries such as China and Turkey.

Heli (2023) investigates the trade in technology products subject to export sanctions and notes that while imports of high-priority battlefield items have dropped significantly, some countries

[1] As of now, the EU has implemented export restrictions on dual use goods, electronic components, machinery components, raw materials, and luxury goods and cars, and import bans on oil, metals and raw materials (European Commission 2025).

have stepped in as alternative suppliers. China has emerged as the largest supplier of sanctioned technology products, including battlefield items, often at premium prices. Central Asian countries such as Kazakhstan, Kyrgyzstan, and Armenia play a key role in re-exporting dual-use goods and luxury items. While Kyrgyzstan has notably specialized in electronic integrated circuits, Turkey, Serbia, and Bosnia have been identified as suppliers of electrical apparatus and diesel engines. Darvas et al. (2024) also find that emerging economies, including Kazakhstan and Turkey, have replaced much of the lost trade in machinery and transport equipment, with evidence of rerouted sanctioned goods.

The United States and the European Union (EU) have adopted secondary sanctions as a key tool to counteract sanction-busting activities, targeting entities in third countries that undermine the effectiveness of primary sanctions. The United States frequently employs such measures, recently sanctioning 217 individuals and entities across multiple jurisdictions for their role in bypassing sanctions against Russia (US Department of the Treasury 2024). While the EU also imposes secondary sanctions, its enforcement is complicated by decentralized implementation, as member states are responsible for applying sanctions. To address this, Directive (EU) 2024/1226 was introduced to harmonize enforcement standards across the bloc (European Parliament and Council of the European Union 2024). Additionally, the EU's extensive trade relationships with key third countries necessitate a diplomatic approach to avoid alienating partners. The 11th and 12th sanction packages emphasize cooperation with these countries to reduce sanction-busting, while enabling export bans where persistent circumvention occurs (Council of the European Union 2023a, 2023b).

Despite their deterrence efforts, sanction-busting remains a challenge for regulators, given the volume of global trade and the sophistication of evasion tactics. This study proposes the application of unsupervised anomaly detection algorithms to financial firm data as a novel method for identifying potential sanction-busters. The rationale is that engaging in sanction-busting activities, such as facilitating the redirection of restricted goods or providing intermediary services, is likely to cause detectable anomalies in a firm's financial reporting. Firms transitioning to such activities may exhibit sudden shifts in financial patterns, such as unusual revenue streams, altered expense distributions, or increases in trade credits

This approach offers several advantages for regulators. First, it enables the screening of a large number of firms, allowing authorities to prioritize investigations on those exhibiting the most suspicious patterns. Second, while customs records already provide information on the sellers of sanctioned goods they may fail to capture firms operating within the Russian customs union or those engaged in mislabeling practices. By leveraging financial anomalies, this method complements existing trade data by identifying firms whose activities might otherwise evade detection. As such, it provides a valuable tool for improving the efficiency and comprehensiveness of regulatory enforcement against sanction evasion.

The paper proceeds as follows: chapter two presents some hypotheses on what patterns to expect in the financial reporting of sanction-busting companies. Chapters three and four describe the data and the detection algorithms applied. Chapter five presents the results and chapter six presents some detected cases to validate the methodology. Chapter seven discusses limitations and chapter eight concludes.

2. Practices of sanction evasion and financial patterns

This chapter examines established methods used to circumvent trade sanctions and explores the potential financial patterns that may arise from these activities. Since the imposition of sanctions, enforcement authorities have continuously adapted their monitoring strategies to counter evasion efforts. To raise awareness among companies and financial institutions, they have published guidance outlining red flags associated with sanction evasion. The European Union has issued detailed recommendations on indicators that may signal an attempt to bypass trade restrictions, emphasizing the importance of due diligence in international transactions (European Commission 2024).

Among the key warning signs identified, the involvement of new or unfamiliar trade partners is particularly notable. Firms with no apparent connection to the sanctioned product or lacking the technical expertise to utilize it may act as intermediaries to disguise the true recipient. Similarly, existing customers placing unusually large orders of restricted goods warrant closer scrutiny. Another red flag involves third-party involvement in payments or shipping, which may indicate the use of rerouting strategies, where goods are officially purchased by one entity but ultimately shipped to an alternative destination, often along a route closer to Russia, such as Belarus (Taran 2022; Yarashevich et al. 2024). A further common evasion tactic includes the direct re-export of sanctioned goods shortly after their initial import into a third country, obscuring the true origin of the transaction (Taran 2022).

While these practices facilitate the continued flow of restricted goods into Russia, they may also leave identifiable traces in the financial records of the companies involved. The expected patterns are as follows:

- **Revenue and Sales Spikes**: Firms engaged in sanction busting might experience a rapid and significant increase in sales or revenues as they resell sanctioned goods to Russian or intermediary firms. The sale of high-value machinery and technology, which was previously inaccessible to sanctioned entities, would provide a lucrative opportunity for these firms. Consequently, a sudden spike in revenues post-sanction imposition could be a red flag.
- **Inventory Spikes**: Firms involved in sanction busting may experience an increase in inventories, especially if they serve as intermediaries holding goods temporarily before exporting them to Russian buyers or other sanctioned entities. An inventory spike following the implementation of sanctions, particularly one that is not aligned with the firm's historical patterns of stockpiling or its operational needs, would be a potential indicator of sanction-busting activity.
- **Plant, Property, and Equipment (PPE) Spikes**: Another anticipated pattern is an increase in PPE. Companies engaging in sanction busting may require additional infrastructure, storage facilities, or specialized equipment to handle the machinery and technology they are acquiring for re-export. Thus, firms involved in sanction busting might report capital expenditures associated with machinery or warehousing, particularly if these assets are necessary for the transportation or short-term storage of sanctioned goods.
- **Trade Credits**: Firms involved in sanction busting may also demonstrate an increase in trade credits, reflecting the financing of machinery and technology purchases. If a firm is purchasing large quantities of sanctioned goods from suppliers in sanctioning countries, this might be recorded as increased trade debts while the resell to Russian firms might trigger an unusual increase in trade credits.

3. Data

The data on firm financials used in this study was obtained from the Bureau van Djik's Orbis database, a comprehensive global resource for firm-level financial information (Bureau van Dijk 2024). The dataset includes firms from seven countries that are of special interest due to their geographic proximity to Russia and/or increased trading activities with Russia since the invasion. These countries are: United Arab Emirates, Armenia, Georgia, Kyrgyzstan, Kazakhstan, Turkey, Uzbekistan.

The initial raw data from these countries consisted of 1139 firms. The scope was restricted to firms that had filed financial reports between 2015 and 2022, which granted the highest availability of data.[2] Additionally, firms must have filed at least one report in 2022, as this marks the beginning of significant sanctions following the Russian invasion of Ukraine. Firms that were directly sanctioned or that were subsidiaries of sanctioned firms were excluded from the sample. This affected eight firms in total.[3] After applying these filters, the final dataset contains 790 firms and 5501 observations, covering financial reports from 2015 to 2022.

The distribution of firms across the seven countries and by firm category is presented in Figure 1A. It is evident that a significant portion of the firms in the dataset are from Turkey and Uzbekistan, with relatively fewer firms from other countries such as Kazakhstan and United Arab Emirates. Furthermore, most of the firms are classified as large firms, with only a few firms from Uzbekistan falling into the medium-sized and small company bracket.[4,5]

Figure 1B illustrates the distribution of firms based on their total assets in 2021. The dataset encompasses a wide range of firm sizes, with the majority reporting total assets below 10 million USD. However, a subset of firms exhibits significantly higher asset values, reaching 1 billion USD or more, representing large-scale enterprises across various industries.

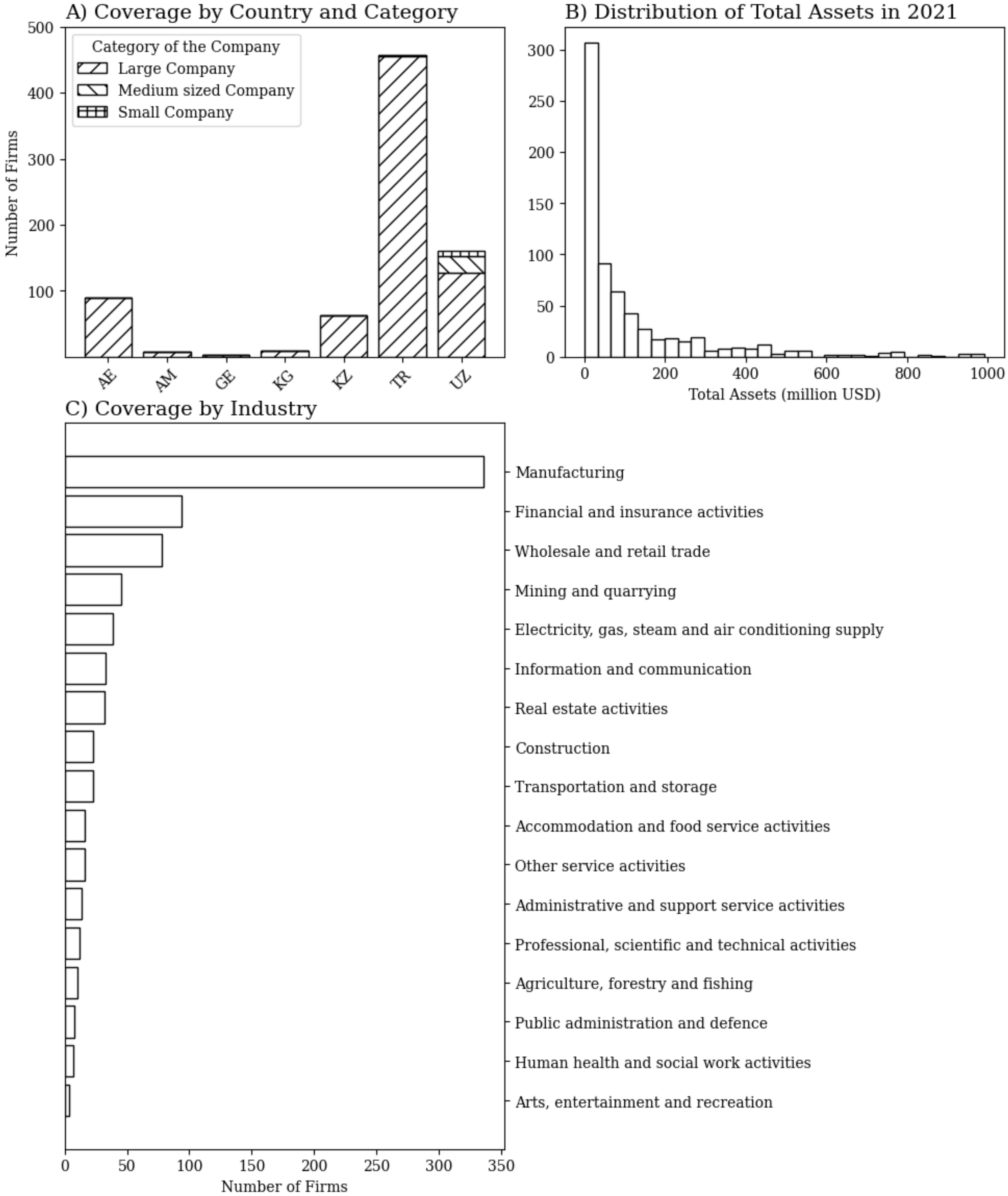
[2] The anomaly detection algorithms used can identify behavioral anomalies, i.e. anomalies considering the within-variation of a firm's financials and contextual anomalies, i.e. anomalies considering variation between firms. The years 2015 to 2022 granted the best coverage for both dimensions.

[3] To identify these firms, the OpenSanctions consolidated database was used, and matches were executed via their API using firm names (local and international) and their addresses (OpenSanctions API 2024).

[4] Obviously, this selection bias has some repercussions on the detection of sanctions evaders. I will discuss these in detail in Chapter 7.

[5] According to the Orbis size thresholds, a large firm has more than 150 employees, more than 26 million USD total assets, and more than 13 million operating revenue. A medium-sized firm ranges between 15 and 150 employees, 2.6 and 26 million USD of total assets, and 1.3 and 13 million USD operating revenue. The rest of the firms are considered small.

Figure 1: Sample Characteristics



Source: Bureau van Dijk (2024), own calculations. Note: Size categories in panel A follow the thresholds applied by Orbis. The histogram in panel B was cut at 1 billion USD for better visualization.

The industry distribution of firms in the dataset is depicted in Figure 1C. The majority of the firms are engaged in manufacturing, followed by firms in the financial and insurance and wholesale and retail trade sectors. In theory, sanction buster could be found in any industry, however, since sanction busting always includes the movement of goods, some sectors appear more likely than others. In particular, the manufacturing, wholesale and retail trade, mining and quarrying, and information and communication sectors could accommodate suspicious firms, as the activities in these sectors either include the movement of goods and machinery, or are related to sanctioned sectors directly.

Based on the hypotheses outlined in chapter two, six numerical variables were selected to identify potential sanction-busting firms: gross sales, total revenue, net profit, net stated inventory, net property and plant equipment, and trade credits.[6] All variables were log-transformed to normalize their distribution. Additionally, first differences were calculated and included as growth rate features. To address occasional missing values, a K-Nearest Neighbors (KNN) Imputer was applied, using five nearest neighbors for the imputation process.[7]

4. Methodology

As need to identify sanction-busting entities has emerged relatively recently, there is a limited body of literature to guide the selection of algorithms specifically for detecting sanction-busting firms. Thus, this study draws from the closely related field of financial fraud detection in financial statements. Although sanction-busting activities are not inherently fraudulent or illegal, identifying such firms shares similarities with detecting financial fraud in financial statements, making this adjacent field a valuable reference point.

Both domains face the challenge of identifying rare, anomalous behaviors within vast datasets. In practice, regulatory bodies cannot inspect entire data populations, instead relying on samples or whistleblowers to detect suspicious firms (Albizri et al. 2019; Ashtiani and Raahemi 2022). This gap in coverage underscores the potential for machine learning (ML) algorithms that can process large datasets to identify entities of interest, providing regulators with an efficient screening tool. Financial fraud and sanction-busting detection share several characteristics:

- Both make extensive use of financial statement data and derived indicators, which serve as inputs for detection algorithms. However, this data is typically noisy, presenting challenges in distinguishing between ordinary firms and those engaging in questionable activities. High data dimensionality, or the "curse of dimensionality", complicates this

[6] In the Appendix is a detailed definition of the variables.
[7] In total, 14 percent of the observations required at least one imputation in the six variables selected for the analysis. Observations that were imputed were tracked and considered during manual checking (see Chapter 6).

further by making fraudulent firms harder to detect amidst the data noise (Hilal et al. 2022; Shahana et al. 2023).

- Evolving patterns in normal and fraudulent behaviors over time result in data drift, where historical models may become less effective in identifying current fraudulent practices (Hilal et al. 2022).
- Both fields suffer from class imbalance, with fraudulent or sanction-busting firms being much less common than typical firms. This rarity can complicate algorithmic detection, particularly for unsupervised approaches (Nonnenmacher and Marx Gómez 2021). Additionally, both domains exhibit cost imbalances, where false positives (normal firms flagged as anomalous) are less costly than false negatives (failing to identify a sanction-busting firm), highlighting the need for a method with low omission errors (Ashtiani and Raahemi 2022; Shahana et al. 2023).

Initially, researchers relied on supervised algorithms like logistic regression, but recent advancements favor machine learning techniques such as neural networks, support vector machines (SVMs), and tree-based methods for classifying fraudulent data (Albizri et al. 2019; Ashtiani and Raahemi 2022; Shahana et al. 2023). However, the lack of labeled data on sanction-busting firms makes a supervised approach unfeasible for this study. Therefore, this paper adopts an unsupervised anomaly detection approach, a less common but emerging methodology in financial fraud detection research, particularly in internal audit contexts where labels are unavailable (Nonnenmacher and Marx Gómez 2021).

Though less prevalent, unsupervised algorithms in fraud detection have notable advantages. They are suited to uncovering previously unknown fraud patterns that might evade more traditional, rule-based detection methods. Scholars highlight the potential of unsupervised techniques like isolation forests, self-organizing maps, and autoencoders for fraud detection because they can operate without labeled data and are resilient against class imbalances. These methods, typically used in internal audit settings, provide valuable insights by identifying unknown anomalies, unintentional errors, or potential fraudulent activities (Nonnenmacher and Marx Gómez 2021; Ashtiani and Raahemi 2022; Hilal et al. 2022).

This study applies three anomaly detection techniques, progressing from simple univariate detection to more complex multivariate methods. The goal is to systematically identify firms exhibiting unusual financial patterns that may indicate potential sanction-busting behavior.

The first approach applies simple univariate anomaly detection by identifying firms with growth rates among the highest observed in the dataset. Specifically, four financial variables are selected based on their relevance to the hypotheses outlined in chapter two: Net profits, net property, plant, and equipment, net stated inventory, and trade credits.[8] Anomalies are defined as observations that fall above or below three standard deviations from the median of each variable's distribution.[9]

The second approach extends anomaly detection to a multivariate setting by employing the Mahalanobis distance, which measures how far a data point is from the center of a multivariate distribution, considering correlations between variables. This method is particularly useful in identifying multidimensional outliers that may not be apparent in individual variables. For a dataset X with mean μ and covariance matrix Σ, the Mahalanobis distance of an observation Xi is given by:

$$D_M(X_i) = \sqrt{(X_i - \mu)^T \Sigma^{-1} (X_i - \mu)} \tag{1}$$

Any observation that lies within the top five percent with the highest distance from the multivariate mean is labeled as an anomaly.[10] This method is widely used in fraud detection, risk management, and industrial quality control due to its ability to account for correlations between variables (Rezapour 2019; Demirhan 2024).

The final method combines the Mahalanobis distance with the Local Outlier Factor (LOF) to refine anomaly detection further (Breunig et al. 2000). The LOF algorithm is a density-based anomaly detection method that identifies observations that deviate significantly from their local neighborhood. Unlike global anomaly detection techniques that assess an observation's deviation from the entire dataset, LOF compares the local density of a point to that of its surrounding neighbors. An observation is considered anomalous if its density is substantially

[8] Since net profits correlates a lot with total revenues and gross sales, a univariate analysis of all three would just produce redundant results. Therefore, total revenues and gross sales were dropped for this exercise.
[9] An alternative approach would be to use median absolute deviations (MAD) from the median instead of standard deviations. MAD is more robust to extreme values and non-normal distributions (Feasel 2022, Aggarwal 2013). However, given the fat-tailed nature of the growth data distribution, applying MAD would likely result in an excessive number of detected anomalies, making the detection overly sensitive and less meaningful for this study.
[10] Usually, observations with a Mahalanobis distance exceeding the 95th percentile of the chi-square distribution with p degrees of freedom (where p is the number of variables) are flagged as anomalies. However, to ensure comparability of the results, I apply a simple 95th percent threshold on the empirical distribution of the Mahalonobis distances.

lower than the densities of its nearest neighbors, suggesting that it is more isolated than expected.

LOF operates by assigning an outlier score to each observation, reflecting the degree to which it deviates from its neighborhood. A score close to 1 indicates that the observation's density is comparable to its neighbors, while higher values suggest increasing levels of deviation. This makes LOF particularly useful in datasets where anomalies are not defined by extreme values in individual variables but rather by unusual relationships across multiple features.

A key design choice in the implementation of LOF is the distance metric used to determine how close two observations are to each other. Many standard implementations use Euclidean distance, which assumes that all variables are independent and have equal importance. However, in high-dimensional financial data, correlations between variables are critical in defining what constitutes an outlier. To account for these correlations, this study employs the Mahalanobis distance as the distance metric within the LOF algorithm. This approach accounts for variable correlations while adapting to local density variations. The combined approach corrects for correlation among variables and also allows for non-linear relationships.

Like most multivariate anomaly detection algorithms, LOF does not inherently provide built-in interpretability mechanisms. However, interpretability is crucial in financial fraud detection and sanction-busting investigations, as regulatory frameworks, such as the EU's General Data Protection Regulation (GDPR), mandate that automated decision-making processes yield explainable and transparent results (EU Commission 2016). To address this interpretability challenge, I employ a rule-based classification algorithm Repeated Incremental Pruning to Produce Error Reduction (RIPPER) using the detected anomalies as labeled training data. RIPPER is a sequential covering algorithm that generates human-readable IF-THEN rules to classify anomalies into meaningful subgroups based on their distinguishing financial characteristics (Cohen 1995). It first induces a rule by iteratively selecting conditions (features) that best separate anomalies from non-anomalies. Then it prunes redundant or overly specific rules to improve generalizability. The final set of IF-THEN rules provides a concise and interpretable framework for categorizing anomalies. Thereby, it serves two purposes in this application: First, it categorizes the detected anomalies into meaningful groups and second it provides a measure for which variables and conditions are the most influential when it comes to finding anomalies in the first place (Salvador et al. 2004; Mutemi and Bacao 2023).

5. Results

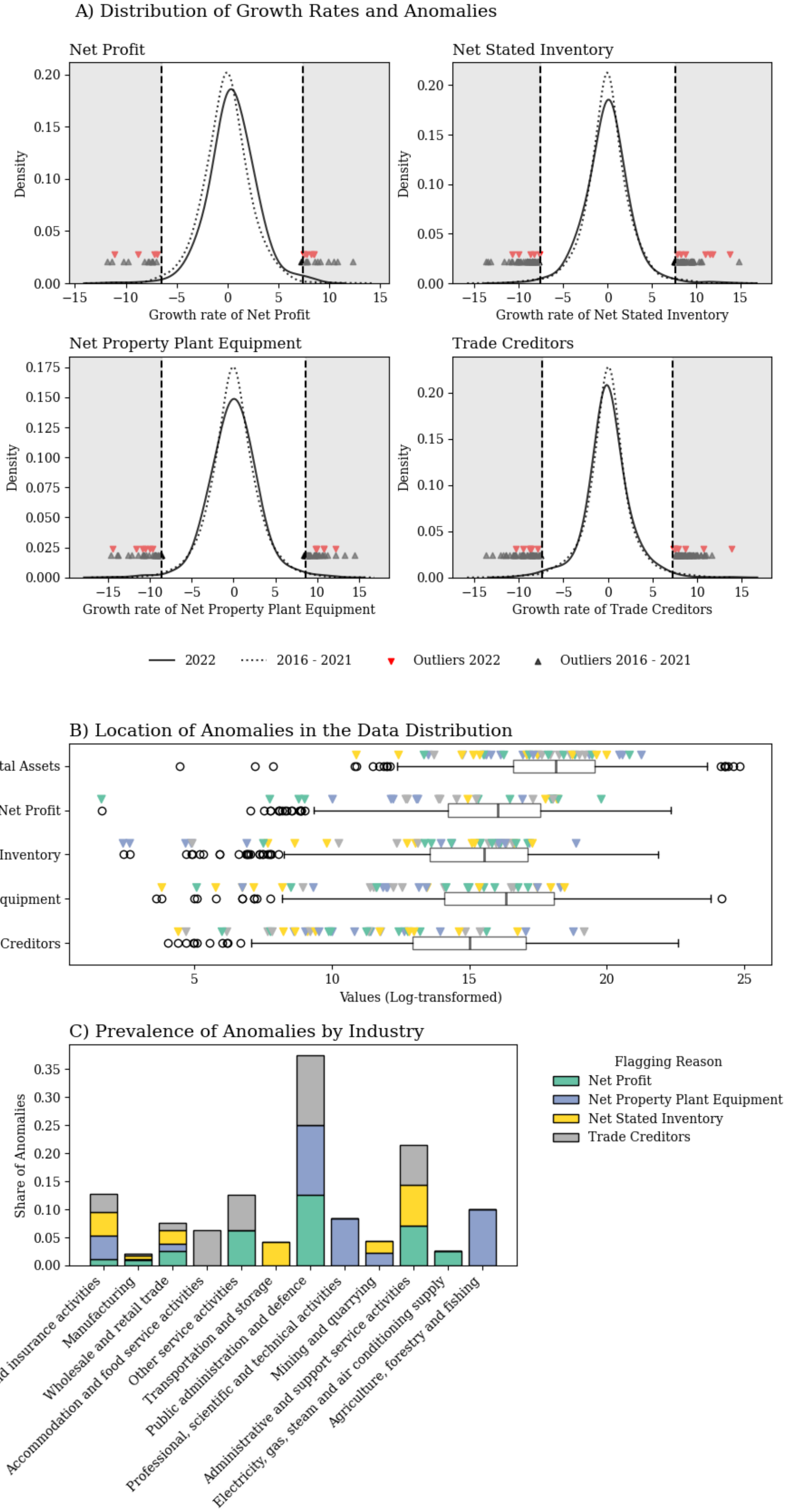
5.1. Univariate Anomaly Detection

The first attempt to identify anomalous firms is to apply univariate anomaly detection methods. For these, the underlying assumption is that the indicators used to identify anomalies are independent from other variables. That way, observations at the outer fringe of the distribution can be identified as anomalies. Figure 2 depicts the distributions of the growth rates of net profits, net stated inventory, net property and plant equipment, and trade credits. Observations that deviate more than three standard deviations from the median are flagged as anomalies. The red triangles represent anomalous firms in year 2022, the black triangles represent anomalous firms of prior years.

Looking at the distribution of the growth rates, the first observation is that the distribution are nearly identical for 2022 compared to prior years. Apparently, on average, the onset of the war in Ukraine and the sanctions against Russia have not had a measurable general effect on the firms in the sample. For all variables, there exist firms with extremely high and extremely low growth rates. However, such anomalies exist for the year 2022 as well as prior years, indicating that these extreme growth rates are not out of the ordinary and thus may not hint at a response to the sanctions regime. Additionally, anomalies can be found at both ends of the distribution and not just at the top end, which would be more in line with the hypotheses made.

Examining the distribution of anomalies in level terms in Figure 2B, it is evident that anomalies are concentrated in the middle and lower ends of the distribution. Notably, extreme growth rates in certain variables tend to correspond with low absolute values. For instance, anomalies flagged due to high profit growth are predominantly found at the lower end of the profit distribution for total assets and all four selected variables. This outcome is expected, as firms with lower baseline values are more likely to exhibit high relative growth rates due to base effects. While such firms could be linked to sanction-busting activities, univariate anomaly detection fails to capture a potentially more critical category of anomalies - those that arise not from extreme values in a single variable, but from complex interactions between multiple variables.

Figure 2: Univariate Anomaly Detection



Source: Bureau van Dijk (2024), own calculations. Note: Anomalies lie more than three standard deviations away from the median.

This limitation highlights the primary drawback of univariate anomaly detection. By analyzing each variable in isolation and assuming no correlation between variables, this approach often misclassifies anomalies, particularly small firms experiencing high growth across multiple variables - a phenomenon that is often expected and benign. At the same time, univariate methods fail to identify firms exhibiting unusual behavior across a combination of variables. For instance, a moderately large firm experiencing a sharp increase in trade credits might appear suspicious when compared to firms of similar size and industry, yet it would not be flagged if evaluated against the overall distribution, which does not account for firm size or sectoral differences. Unlike univariate methods, multivariate techniques account for correlations between variables and can identify local anomalies - firms that appear unusual when compared to their peers with similar characteristics. These methods can uncover subtler patterns, such as firms whose financial behavior deviates from what would be expected given their size, industry, or other attributes. For instance, a firm with moderate revenues and trade creditors but an unusually high increase in net property plant equipment may raise suspicion only when its relationships across variables are considered.

Before moving on to multivariate anomaly detection algorithms, it is worthwhile to examine the prevalence of anomalies by industry, as shown in Figure 2C. One particularly striking feature is the high proportion of anomalies identified in the public administration and defense sector. However, since only a small number of firms from this sector are included in the sample, the absolute number of anomalies remains low despite their high relative share. While the identification of these firms by the univariate anomaly detection exercise is certainly notable, it is also somewhat redundant, as firms operating in this sector would already be subject to heightened scrutiny, regardless of the outcome of any anomaly detection method.

The next chapter will present anomalies detected using multivariate methods, such as Mahalanobis distance and LOF. These approaches are better suited to capturing the interactions between variables and provide a more nuanced perspective on potential sanction-busting activity.

5.2. Multivariate Anomaly detection

Figure 3A shows the distribution of feature values for the top ten variables that contribute to the anomalies identified by the Mahalonobis distance. The ranking of the variables is determined by the RIPPER algorithm and includes a mix of absolute measures, such as net property plant equipment and trade credits, as well as growth rates, such as gross sales growth and net stated inventory growth.[11] The gray box plots represent the normal data distribution, while the white box plots represent anomalies in 2022. Generally, the distribution of the anomalous firms is much wider, often including many extreme values, similar to the results from univariate anomaly detection. However, as noted earlier, the strength of a multivariate approach lies in its ability to detect anomalies based on interactions between variables. To illustrate which interactions have led to firms being flagged as outliers, Figure 3B presents rules derived from a RIPPER algorithm. The algorithm was trained using the anomaly flags as labels in a supervised classification. Each rule describes combinations of feature thresholds (in percentiles of the data distribution) that characterize anomalous firms, along with the number of firms covered by the rule (support) and the precision of the rule in flagging anomalies (the share of flagged firms that are anomalous).

Most of the rules derived from the RIPPER algorithm do not appear particularly suspicious. Similar to the results from univariate anomaly detection, several rules primarily flag relatively small firms with low growth rates and low absolute values. For example, the most frequently supported rule (Rule 1) identifies only firms with very low revenue in 2022. In contrast, Rules 9 to 11 highlight firms exhibiting high inventory growth combined with medium trade credits or gross sales as anomalies. Cases like these may warrant closer scrutiny, as they could indicate unusual business behavior, such as sudden stockpiling for imminent re-export.

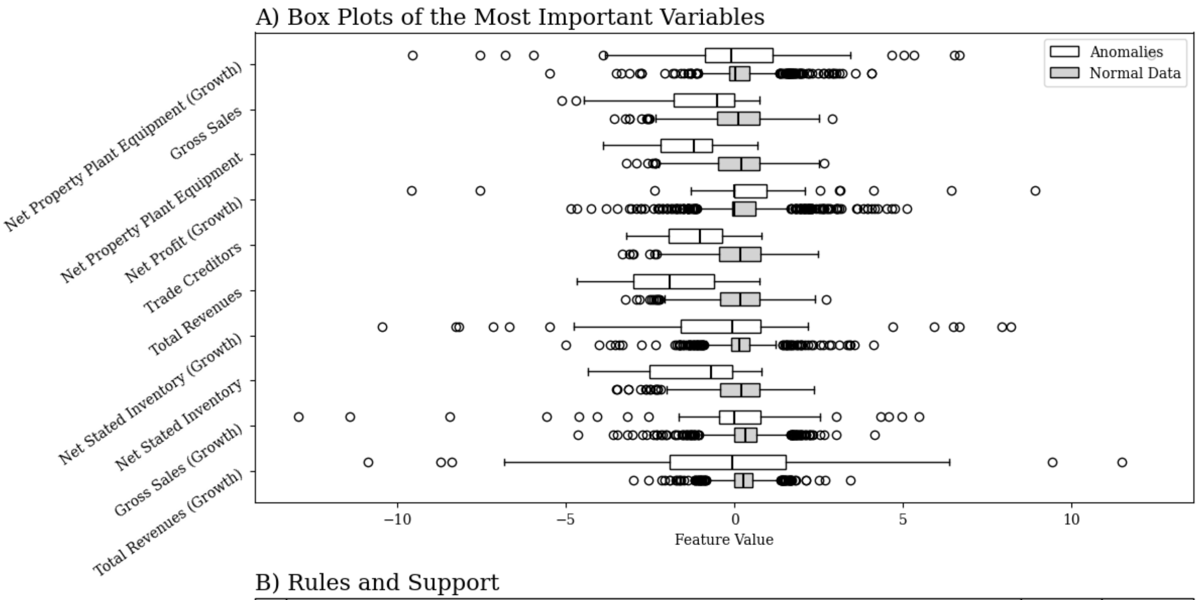
While the Mahalanobis distance is a good metric for detecting global anomalies by accounting for correlations between variables, it struggles with varying densities and non-linear relationships between features. LOF, in contrast, is designed to detect local anomalies by comparing the density of a data point to that of its neighbors. By combining these methods, it is possible to account for the correlation between variables while also focusing on local patterns of irregularity.

Figure 4A illustrates the distribution of anomalies and normal data, along with the rule sets derived from the LOF anomaly detection algorithm. Examining the variable distributions, anomalies display a wide range of values, spanning both extremes. Unlike anomalies identified in the univariate exercise, the distribution of LOF-derived anomalies is not skewed toward smaller values and exhibits a median similar to that of normal data. Similar to Mahalanobis distance-based detection, growth rates play an equally important role in identifying anomalies.

[11] The ranking is based on how often the RIPPER algorithm picks a variable to construct identifying IF-THEN rules. The more often a variable is picked, the higher the importance ranking.

This is evident from the fact that five out of the top ten contributing features remain growth-related variables.

Figure 3: Anomalies identified by Mahalonobis distances



B) Rules and Support

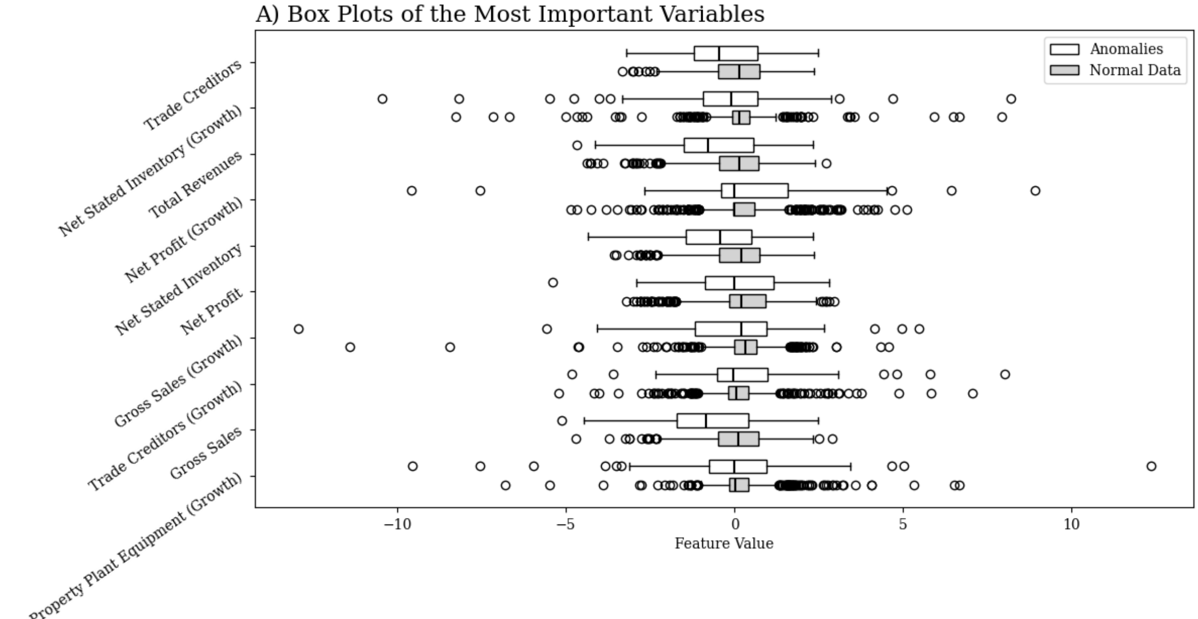
Nr.	Rule	Support	Precision
1	Total Revenues=<0.024	23	0.78
2	Net Stated Inventory=<0.042 & Trade Creditors (Growth rate)=>0.94	7	0.86
3	Total Revenues=0.024-0.089 & Net Stated Inventory=<0.042 & Total Revenues (Growth rate)=<0.054	6	0.83
4	Net Stated Inventory=<0.042 & Total Revenues (Growth rate)=>0.97	5	1.0
5	Total Revenues=0.024-0.089 & Total Revenues (Growth rate)=0.24-0.39 & Gross Sales (Growth rate)=0.098-0.3	3	0.67
6	Trade Creditors=0.08-0.16 & Net Profit (Growth rate)=0.89-0.95	3	0.33
7	Total Revenues (Growth rate)=<0.054 & Gross Sales=0.68-0.79	3	1.0
8	Trade Creditors=<0.08 & Net Profit (Growth rate)=>0.95 & Net Property Plant Equipment=0.069-0.14	2	1.0
9	Net Stated Inventory (Growth rate)=>0.95 & Trade Creditors=0.41-0.53 & Net Property Plant Equipment=<0.069	2	1.0
10	Net Stated Inventory (Growth rate)=>0.95 & Trade Creditors=0.08-0.16 & Gross Sales=0.16-0.28	2	0.5
11	Net Stated Inventory (Growth rate)=>0.95 & Gross Sales=0.68-0.79 & Net Profit (Growth rate)=0.51-0.75	2	1.0
12	Gross Sales (Growth rate)=0.098-0.3 & Net Stated Inventory=0.45-0.55 & Net Stated Inventory (Growth rate)=>0.95	1	1.0
13	Total Revenues (Growth rate)=>0.97 & Gross Sales (Growth rate)=0.83-0.88	1	1.0

Sources: Bureau van Dijk (2024), own calculations. Note: Variables in levels are in logarithms. Additionally, both variables in levels and growth rates are normalized to a mean of zero and a standard deviation of one.

Examining the rules derived from the RIPPER algorithm, the overall pattern differs significantly from the rules associated with Mahalanobis distances. While some rules still identify small businesses with exceptionally low values across multiple dimensions, there is now a greater prevalence of rules capturing firms with a mix of high and medium values or consistently high values.

Figure 4: Anomalies identified by LOF

A) Box Plots of the Most Important Variables



B) Rules and Support

Nr.	Rule	Support	Precision
1	Total Revenues=<0.048 & Trade Creditors=0.089-0.18	10	0.4
2	Total Revenues=0.048-0.12 & Net Profit (Growth rate)=>0.95	9	0.67
3	Trade Creditors (Growth rate)=>0.94 & Net Profit=>0.94	7	0.86
4	Net Property Plant Equipment (Growth rate)=>0.96 & Net Stated Inventory=<0.073	6	0.5
5	Net Profit=>0.94 & Net Property Plant Equipment (Growth rate)=0.069-0.18	6	0.33
6	Net Stated Inventory=<0.073 & Gross Sales (Growth rate)=>0.96	6	0.5
7	Total Revenues (Growth rate)=<0.076 & Trade Creditors (Growth rate)=>0.94	5	0.4
8	Net Profit=>0.94 & Gross Sales=0.6-0.72	5	0.6
9	Net Property Plant Equipment (Growth rate)=<0.069 & Trade Creditors (Growth rate)=<0.11 & Net Profit (Growth rate)=<0.11	4	1.0
10	Gross Sales=<0.051 & Net Stated Inventory (Growth rate)=0.057-0.2	4	0.75
11	Net Profit=>0.94 & Net Property Plant Equipment (Growth rate)=<0.069	4	0.75
12	Net Stated Inventory (Growth rate)=<0.057 & Gross Sales=>0.92	4	1.0
13	Net Stated Inventory=<0.073 & Trade Creditors (Growth rate)=0.88-0.94	3	0.67
14	Trade Creditors (Growth rate)=>0.94 & Gross Sales (Growth rate)=0.07-0.28	3	1.0
15	Net Stated Inventory (Growth rate)=<0.057 & Net Property Plant Equipment (Growth rate)=<0.069 & Gross Sales (Growth rate)=0.07-0.28	3	1.0
16	Net Property Plant Equipment (Growth rate)=0.91-0.96 & Net Profit=>0.94 & Net Profit (Growth rate)=0.83-0.89	3	0.67
17	Gross Sales (Growth rate)=<0.07 & Total Revenues=<0.048 & Net Property Plant Equipment (Growth rate)=<0.069	3	1.0
18	Gross Sales=<0.051 & Trade Creditors=0.089-0.18 & Net Stated Inventory=0.073-0.17	3	0.67
19	Gross Sales (Growth rate)=<0.07 & Trade Creditors (Growth rate)=0.11-0.21 & Gross Sales=<0.051	2	1.0
20	Trade Creditors (Growth rate)=>0.94 & Total Revenues=0.82-0.92	2	0.5
21	Gross Sales (Growth rate)=<0.07 & Gross Sales=0.82-0.92	2	0.5
22	Net Property Plant Equipment (Growth rate)=0.91-0.96 & Net Stated Inventory (Growth rate)=<0.057 & Gross Sales (Growth rate)=>0.96	1	1.0
23	Net Stated Inventory (Growth rate)=<0.057 & Net Profit (Growth rate)=0.76-0.83 & Gross Sales=0.82-0.92	1	1.0
24	Trade Creditors=0.27-0.37 & Net Stated Inventory=0.38-0.5 & Net Profit=0.72-0.81	1	1.0
25	Trade Creditors (Growth rate)=<0.11 & Net Profit (Growth rate)=>0.95 & Total Revenues=0.24-0.36	1	1.0
26	Trade Creditors=0.18-0.27 & Net Property Plant Equipment=<0.073 & Net Stated Inventory=0.17-0.26	1	1.0

Sources: Bureau van Dijk (2024), own calculations. Note: Variables in levels are in logarithms. Additionally, both variables in levels and growth rates are normalized to a mean of zero and a standard deviation of one.

For instance, Rule 2 identifies firms that experienced extreme profit growth while maintaining moderate revenue levels in 2022, whereas Rule 14 highlights firms with high trade credit growth in 2022 but only moderately low sales growth overall. Rule 3, on the other side, points towards firms with exceptionally high trade credit growth and a very high level of net profit.

The results of both the Mahalanobis distance and LOF approaches demonstrate their distinct advantages and limitations in detecting anomalies. The Mahalanobis distance effectively identifies global anomalies by accounting for correlations between variables but frequently flags firms with extreme values across multiple dimensions, many of which may not indicate suspicious activity. In contrast, LOF complements this by capturing local anomalies, identifying firms that deviate from their immediate peers in terms of density. At first glance, the LOF results appear more aligned with behaviors potentially indicative of sanction-busting, as they highlight firms with unusual patterns relative to their specific contexts.

6. Plausibility

In this chapter, I examine the detected anomalies to assess the plausibility of their connection to sanction-busting activities. To this end, I focus on three classification rules derived by the RIPPER algorithm, which plausibly indicate sanction evasion. The analysis follows a three-step approach: (i) selecting the most relevant rules, (ii) examining the development of balance sheet items over time, and (iii) conducting a targeted web search on the identified companies.

Based on the hypotheses outlined earlier, Rules 2, 3, and 20 derived from the LOF anomalies describe patterns potentially associated with sanction-busting behavior. These patterns are characterized by high revenue growth combined with either high trade credit growth or high profit growth. Applying these three rules to the dataset yields 16 companies. Some of these cases represent false positives, meaning that they matched the RIPPER-derived rules but were not flagged as anomalies by the LOF algorithm. Others exhibited high growth rates due to base effects, rather than genuine irregularities. Consequently, 8 out of the 16 companies were selected for further investigation via web search.

The selected firms include three investment holdings, a leasing company, a manufacturer of electronic components, a fertilizer producer, and two firms from the oil sector. The following section presents a selection of three cases where a basic web search revealed economic ties to Russia since the invasion of Ukraine.

Figure 5 presents the first case study, ADNOC Drilling, a subsidiary of the Abu Dhabi National Oil Company (ADNOC). As one of the largest national drilling companies in the Middle East by rig fleet size, ADNOC Drilling serves as the exclusive provider of drilling and rig-related services to the ADNOC Group, operating both onshore and offshore in Abu Dhabi (ADNOC Drilling 2025).

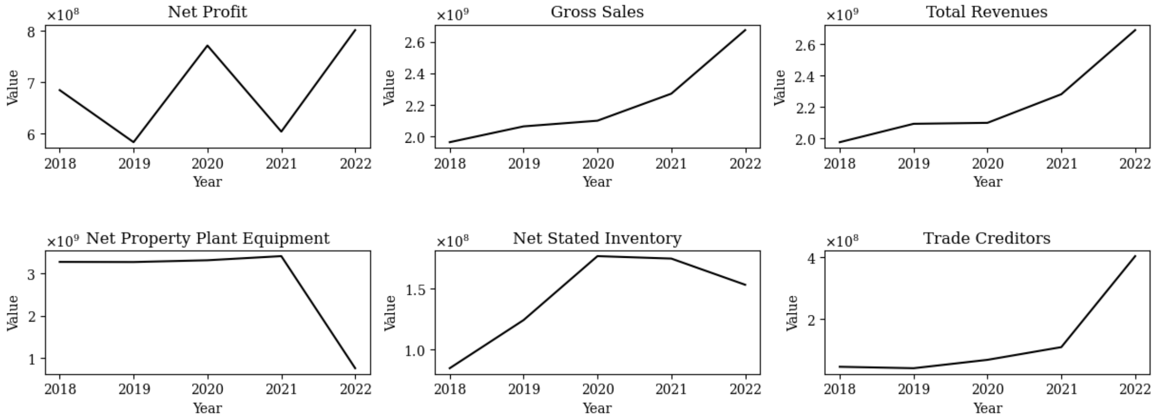
During the algorithmic screening, ADNOC Drilling was flagged due to a significant increase in trade credits in 2022, combined with relatively high profit levels. Analyzing the evolution of sales and revenue, a notable increase from 2021 to 2022 is observed, accompanied by a decline in property, plant, and equipment. While this pattern could suggest the sale of drilling machinery at a premium in 2022, further investigation via web search revealed an alternative connection to the Russian oil sector. Specifically, in November 2022, a shipment of 700,000 barrels of Arctic crude oil, loaded by Russia’s Gazprom, was delivered to an ADNOC refinery (Benoit and Summer 2023).

Figure 5: ADNOC Drilling

A) Company Information

Name	Adnoc Drilling
Rule	Trade Creditors (Growth rate)=>0.94 & Net Profit=>0.94
Country	United Arab Emirates
Country Controller	United Arab Emirates
Country Shareholder	United Arab Emirates
Primary Industry V2	Support activities for petroleum and natural gas extraction
Incorporation	1981

B) Indicators Over Time



Source: Bureau van Dijk (2024), own calculations.

Al Seer Marine Supplies & Equipment Company P.J.S.C., headquartered in Abu Dhabi, is a maritime organization that provides a diverse range of services, including commercial shipping, yacht management, boat building, and unmanned vessel platforms (Al Seer Marine 2025).

Al Seer presents an interesting case, as it was flagged due to a significant increase in expected trade credit growth in 2022, combined with high revenue levels in the same year. The imputed trade credit value likely results from the extraordinarily high growth rates observed in net property, plant, and equipment, as well as net stated inventory. Under these conditions, a missing value in trade credits might warrant closer scrutiny. Taken together, the figures may indicate a potential fleet expansion and the extension of services to Russian maritime companies.

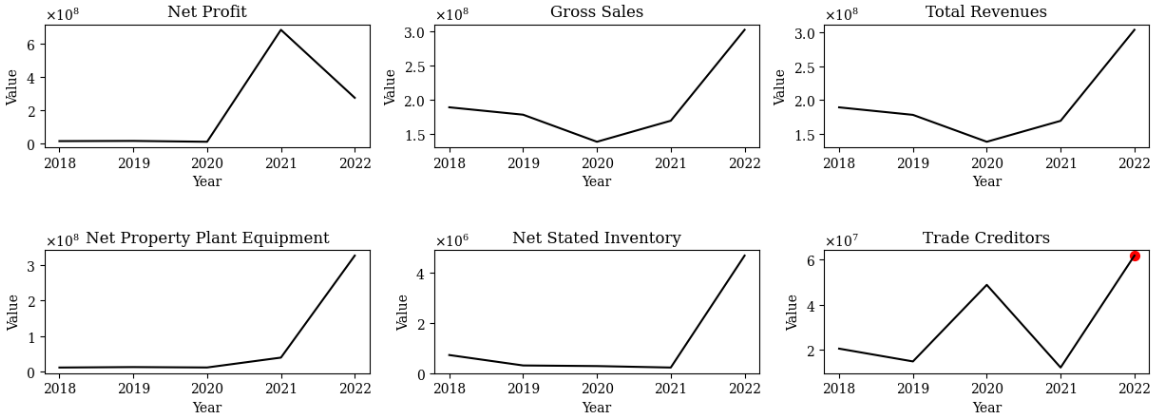
A web search confirmed business transactions between Al Seer Marine and Russian entities. In early 2023, the company acquired four vessels from Sovcomflot, a Russian state-owned shipping company that has been subject to international sanctions. This acquisition was positioned as part of Al Seer Marine’s fleet expansion strategy (Wijaya 2022). Additionally, in June 2024, reports indicated that tankers owned by companies registered in the United Arab Emirates, including Al Seer Marine, were involved in transporting Russian petroleum products from Baltic Sea ports, despite existing sanctions (Black Sea Institute of Strategic Studies 2024).

Figure 6: Al Seer Marine Supplies & Equipment Company

A) Company Information

Name	AL Seer Marine Supplies & Equipment Company P.J.S.C.
Rule	Trade Creditors (Growth rate)=>0.94 & Total Revenues=0.82-0.92
Country	United Arab Emirates
Country Controller	Unkown
Country Shareholder	United Arab Emirates
Primary Industry V2	Agents involved in the sale of machinery, industrial equipment, ships and aircraft
Incorporation	2003

B) Indicators Over Time



Source: Bureau van Dijk (2024), own calculations. Note: Red dots indicate imputed values.

Emlak Varlik Kiralama A.S. is a special purpose vehicle (SPV) established in 2019 in Turkey. The company functions as an asset leasing entity for Türkiye Emlak Katilim Bankasi, primarily facilitating the issuance of lease certificates to support the bank’s participation banking activities (Emlak Varlik Kiralama 2025).

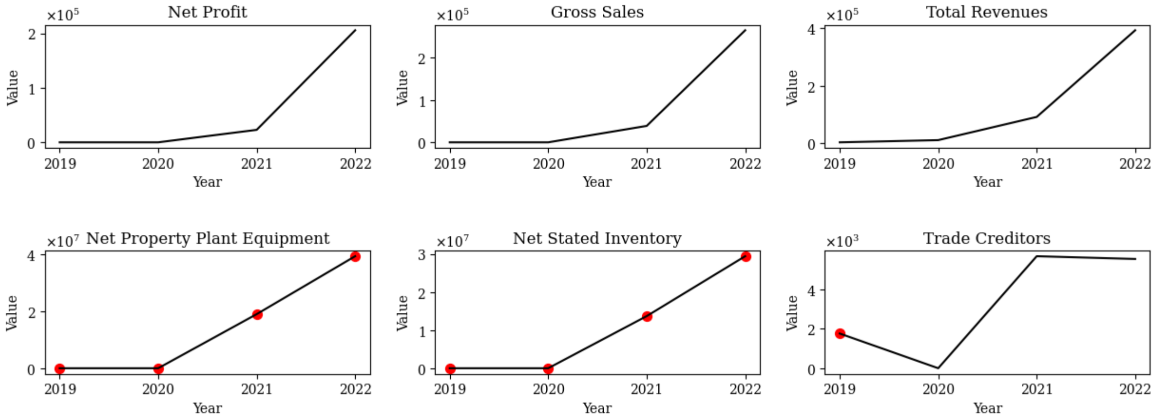
During the algorithmic screening, Emlak Varlik Kiralama A.S. was flagged due to a sharp increase in net profit growth in 2022.[12] A web search uncovered indirect links to Russian financial transactions through the company's parent institution, Türkiye Emlak Katilim Bankasi. Reports suggest that the bank has continued to facilitate payments in Turkish lira and Russian rubles to support Russian-Turkish trade, particularly following restrictions imposed by other Turkish banks on transactions in U.S. dollars and euros (KSI Institute 2025).

Figure 7: Emlak Varlik Kiralama A.S

A) Company Information

Name	Emlak Varlik Kiralama A.S
Rule	Total Revenues=0.048-0.12 & Net Profit (Growth rate)=>0.95
Country	Türkiye
Country Controller	Unkown
Country Shareholder	Unkown
Primary Industry V2	Renting and leasing of other machinery, equipment and tangible goods n.e.c.
Incorporation	2019

B) Indicators Over Time



Source: Bureau van Dijk (2024), own calculations. Note: Red dots indicate imputed values.

While none of the identified firms can be definitively classified as sanction busters based on publicly available information, the findings suggest that the applied anomaly detection methods effectively highlight firms warranting further investigation. Among the 790 firms with available financial data for 2022, the LOF algorithm flagged 62 as anomalous, of which 16 were selected for an initial manual screening. From this subset, 8 firms underwent in-depth web-based research, ultimately revealing economic ties with Russia since the invasion of Ukraine in three cases.

Given that unsupervised anomaly detection algorithms are typically prone to high false-positive rates, the observed conversion rate from flagged anomalies to firms with confirmed economic

[12] No data was available for net property, plant, and equipment, or net stated inventory. Given the company's industry, this absence is not necessarily concerning, as financial corporations typically do not maintain inventory or significant physical assets.

connections to Russia is noteworthy. These results indicate that the chosen methodology can effectively narrow down a large dataset to a smaller set of high-risk candidates, reducing the workload for further investigative efforts.

Furthermore, the presented findings are limited by the constraints of publicly accessible information. The analysis relies primarily on financial disclosures and simple web searches, which may only capture a fraction of a firm's true activities. Official government bodies and regulatory agencies possess access to customs and transaction data, beneficial ownership records, and other confidential sources, which could provide a more comprehensive assessment of potential sanction violations. Thus, while the algorithmic approach alone does not provide definitive proof of sanction evasion, it serves as a valuable screening tool to identify firms that merit further scrutiny by authorities with greater investigatory resources.

7. Limitations

The approach presented in this paper is subject to several limitations related to both data quality and conceptual choices. The dataset used is highly heterogeneous, encompassing firms of different sizes, industries, and countries, which impacts both the validity of the anomaly detection results and the generalizability of the findings. Additionally, the data is sparse, and for some firms, few similar neighbors exist within the sample, making anomaly detection challenging. In particular, this can lead to some firms being falsely flagged as anomalies but also to firms falsely identified as normal firms, due to deflated densities in the data. Furthermore, the Orbis dataset is unrepresentative for many countries in the sample, which is not necessarily a problem for the anomaly detection but limits the ability to generalize findings.

Another potential limitation arises from the selection of sample years. While all algorithms are applied to the entire dataset, only anomalies identified in 2022 are further reviewed and investigated. This design choice is based on the rationale that anomalies in 2022 should be evaluated in relation to all other observations, including each firm's historical financial records. However, the global COVID-19 pandemic in 2020 and 2021 likely introduced financial distortions that may affect the baseline for anomaly detection. The economic disruptions during this period resulted in unusual financial patterns, including sharp revenue declines, supply chain interruptions, and liquidity constraints, which may have led to a higher prevalence of irregular financial records in the dataset. As a consequence, the presence of pandemic-induced anomalies could obscure or dilute the detection of genuine sanction-busting anomalies, potentially leading to false negatives, where firms engaged in sanction evasion remain undetected.

Conceptually, the approach relies on several critical assumptions that may not hold. For instance, unsupervised algorithms typically assume that anomalous behavior is rare and distinguishable from normal behavior, yet, the prevalence of sanction-busting among firms is unknown. Therefore, in case sanction-busting behavior is less prevalent than five percent the firms, the presented algorithms produces a high number of false positives. Moreover, the core assumption of this paper is that sanction-busting leads to measurable changes in balance sheet items that differentiate such firms from their peers. If this assumption is invalid, the presented approach loses its viability. In such a case, alternative methods, such as combining anomaly detection with qualitative case studies or leveraging external datasets like trade or customs data, may be required to identify sanction-busting behaviors more effectively.

While the unsupervised approach might uncover yet unknown identifiers of sanction-busting activities, the analysis does not provide any direct evidence of sanction-busting. To validate these findings, customs data from multiple countries - or at least from Russia - would be necessary, but such data is unfortunately not publicly available. The algorithms can only identify firms that deviate from expected patterns based on their peers, pointing to potentially suspicious firms without proving intent or confirming illicit activity. Furthermore, some of the detected suspicious patterns could be entirely unrelated to sanction-busting. Such patterns may arise purely by coincidence or as a result of distortions caused by the unrepresentative sample. For example, the dataset is likely affected by self-selection biases, as the Orbis database includes mostly large firms for the included countries, while sanction-busting may be more common among smaller firms that are underrepresented. The small sample size further exacerbates selection biases, increasing the likelihood that some anomalies reflect the sparsity of the data rather than meaningful irregularities.

8. Conclusion

This study investigates the potential of unsupervised anomaly detection algorithms in identifying firms engaged in sanction-busting activities. By leveraging financial data from firms operating in countries with potential trade links to Russia, the analysis demonstrates that financial anomalies can serve as indicators of suspicious economic behavior, warranting further investigation by regulators. The application of three anomaly detection techniques - univariate anomaly detection, Mahalanobis distance, and LOF - revealed several firms exhibiting unusual financial patterns. While univariate anomaly detection primarily flagged small firms with extreme growth rates, multivariate methods provided a more nuanced perspective by identifying firms with atypical financial behavior relative to their industry peers. The combination of

Mahalanobis distance and LOF proved particularly effective, as it accounted for both high correlation between variables and non-linear relationships in the dataset.

To enhance interpretability, a rule-based classification using the RIPPER algorithm was applied, allowing anomalies to be categorized into distinct groups. This process highlighted firms exhibiting suspicious combinations of revenue spikes, inventory buildup, and trade credit growth - patterns that align with expected sanction-busting strategies. A subsequent web search of the most suspicious cases confirmed economic ties with Russia in three out of eight selected firms. These results suggest that the applied methodology effectively narrows down high-risk candidates for further scrutiny, supporting its potential as a screening tool in regulatory and compliance efforts.

The findings underscore the value of anomaly detection for identifying firms involved in sanction evasion. Given that unsupervised machine learning approaches typically generate high false-positive rates, the observation that three out of eight web-searched firms exhibited confirmed economic links to Russia suggests a very promising conversion rate. However, the approach remains subject to several limitations. The Orbis database, while comprehensive, does not fully represent all firms operating in relevant jurisdictions, particularly smaller enterprises that may be more active in sanction-busting. The necessity of imputing missing financial data introduces potential biases, and the core assumption that sanction busting activity manifests as detectable financial anomalies may not always hold. Firms engaging in sanction circumvention could employ accounting strategies to obscure their financial position, making detection more challenging. Furthermore, the absence of external validation data limits the ability to confirm suspected cases definitively, as publicly available information may not capture the full scope of illicit financial flows. Access to customs records, transactional data, and corporate ownership structures would significantly enhance the robustness of the findings.

Future research should explore hybrid approaches that combine unsupervised and semi-supervised learning to reduce false positives while improving detection accuracy. Network-based anomaly detection, which considers corporate ownership structures and transactional relationships rather than financial anomalies alone, is likely to produce more reliable results. However, for these methods to be effective, there is a critical need for validation mechanisms that can confirm whether the firms identified by anomaly detection are genuinely engaged in sanction-busting activities or are false positives. Without an external benchmark, such as customs records, trade data, or government investigations, assessing the accuracy of algorithmic screening remains challenging.

Appendix

Variable	Definition
Gross Sales	Amount of total sales unadjusted for the costs related to generating them. It is calculated by adding all sales receipts before discounts, returns and allowances for the period. It was picked over other sales indicators due to better coverage.
Total Revenue	Amount of income generated from the company's sale of goods and services as well as other sources of income from core business functions.
Net Profit	Amount of profit (loss) after tax minus minority interests, other adjustments, extraordinary items after tax and preferred dividends.
Net stated Inventory	Amount of goods and materials after adjustments that a business holds for resale, production or utilization.
Net Property Plant and Equipment	Value of all buildings, land, furniture, and other physical assets that a business has purchased to run its business. These are net of accumulated depreciation.
Trade Creditors	Trade payables to suppliers and contractors that provided goods and services to the company on credit terms in their ordinary course of business.

Source: WRDS (2024).

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