“Not a dog. Not a wolf. All he knows is what he’s not”:

detection indicators for Buffer Companies involved in complex fiscal frauds

Abstract

Buffer Companies (BCs) are used in complex fiscal fraud, where they play a role in obscuring the link between illicit transactions and their final beneficiaries. They help extend the fraud chain and shield Real and Operating Companies (ROCs) from direct involvement, while these latter ultimately benefit from illicit activities. This makes detection more difficult for AML functions of financial intermediaries. In this study, we build and analyze a unique dataset of BCs, sourced from Italian Supreme Court rulings and suspicious transaction reports submitted to the Italian Financial Intelligence Unit (UIF). Our findings reveal that BCs exhibit an “amphibious” behavior, combining features of both Shell Companies (SCs) and ROCs. We develop a composite indicator for identifying potential BCs, offering a screening tool for AML functions of financial intermediaries. This tool can support more effective detection and timely reporting of suspicious entities to UIF, thereby reducing the risk associated with serving potential criminal clients.

JEL Classification: H26, H32, K42, L22

Keywords: tax evasion and avoidance, fiscal fraud, money laundering, buffer companies, financial statements

Contents

1. Introduction, literature and motivation

Fiscal fraud is particularly appealing to criminal organizations because, as stated by a cooperative witness during an investigation conducted by the European Public Prosecutor's Office (EPPO), *"you risk nothing, you just need to find an accountant, a good lawyer and someone who knows how to talk, and you can make big money"*. In contrast, drug trafficking is seen as less attractive, *"with its very severe prison sentences in the event of conviction"*. Moreover, drug-related crimes draw significant public attention, often prompting a strong response from authorities (EPPO, 2024).

This is not the case for white-collar crimes such as fiscal frauds — a key predicate offence for money laundering — which are harder to detect, as they typically involve no direct victims who can report the crime. One of the most widespread form of fiscal fraud is the Value Added Tax (VAT) fraud, which caused an estimated loss of approximately €11.5 billion in cases investigated by the EPPO during 2023, showing a 71% increase compared to 2022. To provide some context, in 2023 approximately one fifth of the offences investigated by the EPPO involved the most serious forms of VAT fraud, i.e., those affecting two or more participating EU Member States, causing total damage of at least €10 million (EPPO, 2024). What is more, according to the European Commission's estimates provided in the 2023 VAT gap report, VAT losses across EU Member States were estimated at €61 billion in 2021, compared to €99 billion in 2020. The overall amount was particularly high in Italy, where the estimated VAT gap for 2021 exceeded €14 billion, more than double the figure reported for Germany, despite Germany being a larger economy (CASE et al., 2023). In addition, fiscal fraud accounts for a substantial share of the suspicious transaction reports (STRs) received by the Financial Intelligence Unit for Italy (UIF), representing approximately one-fifth of all STRs in both 2022 and 2023. Of this share, more than a quarter was connected to false invoicing (UIF 2023 and UIF 2024).

Fiscal fraud can be of multifaceted nature and typically happens when individuals or businesses deliberately provide false information (or fail to report information) to reduce tax liability or claim unwarranted tax credits. More specifically, fiscal fraud can arise when individuals pay for goods or services in cash and do not report the related transactions, or when businesses build complex carousel schemes to launder money and obtain fictitious tax credits. The main effects are on competition and on the government budget. Indeed, firms involved in fiscal fraud obtain an unfair advantage by reducing their tax bills, and the resulting reduction in the tax base is a serious political concern, which limits government resources for essential public goods such as education or health care. Given that VAT accounted for approximately 27 percent of the total yearly tax receipts in the EU in 2021 (CASE et al., 2023), VAT fraud, in particular, represents a serious threat to public finances.

The so-called Shell Companies (SC),[1] also known as "Missing Traders" in VAT frauds, play a crucial role in tax fraud schemes, essentially by issuing false invoices for non-existing operations. There is broad consensus among scholars, practitioners, and Law Enforcement Agencies (LEAs) — such as the Italian Guardia di Finanza (GdF) — on the core characteristics of SCs. These companies typically report high turnover, despite not engaging in real business activities: they usually lack machinery and production means, such as employees, which is reflected in low levels of tangibles assets and a labor cost close to zero. At the same time, SCs tend to avoid participation in financial markets and prefer to circumvent bank scrutiny, since they do not need external capital to support their non-existent operations. In order to remain undetected, SCs usually report a shorter lifespan compared to their peers (GdF, 2017; UIF, 2020; Pellegrini *et al.,* 2020; Casazza and Lupo, 2021; Pellegrini, 2024a; Pellegrini, 2024b). Furthermore, they exhibit a high correlation between costs and revenues, alongside significant revenue volatility, which further distinguishes them from legitimate firms (Fabrizi *et al.,* 2017).

In more complex illicit schemes, another type of company, known as Buffer or Filter Company (BC), may be involved. The name BC stems from the fact that these entities are often positioned between SCs and Real and Operating Companies (ROCs) — the latter being the ultimate beneficiaries of the fraud scheme. BCs help the fraud perpetrators in two main ways: first, by lengthening the fraud chain, thus making detection more difficult; second, by shielding ROCs from direct involvement in the illegal activities (Antonacchio, 2005; FATF, 2007; Borselli, 2011; Frunza, 2013; GdF, 2017; UIF, 2020; Casazza and Lupo, 2021). It is worth noticing that BCs may be sometimes unaware of the fraud (Antonacchio, 2005; Borselli, 2011; Borselli *et al.*, 2015) which, particularly in larger companies, may be perpetrated by middle management. The role of BCs is also well-documented in Italian case law.[2]

In the economic crime literature, there are few qualitative studies that describe the basic nature of BCs, defining them as "*fully compliant traders carrying out regular business outside the fraud*" (Borselli, 2011 p. 8), or describing their activities such as buying and reselling goods below market prices without incurring business risk (Antonacchio, 2005; Casazza and Lupo, 2021). However, to the best of our knowledge, no quantitative studies have examined the financial statement characteristics of BCs. In contrast, SCs' financial statements have been extensively studied (Pellegrini *et al.*, 2020).

[1] Shell companies are firms that can be used for lawful purposes like reverse merger, financing foreign operations, protection against bankruptcy risks or for unlawful goals like tax evasion, bribery, corruption, money laundering, etc. (*Tiwari et al.*, 2020).

[2] See, for example, sentence no 7299/2021 (fifth civil section) and ordinances no 2916/2022 (fifth civil section) and 19214/2022 (sixth civil section). Source: Cassazione Sentences from 2018 – 2023 - [Sentenze Cassazione (giustizia.it).](https://www.giustizia.it)

Against this background, the aim of our work is to answer the following two research questions:

1. What are the financial statement characteristics of BCs?
2. Based on these characteristics, is it possible to provide red flags and develop a composite indicator to identify potential BCs among the customer base of Financial Intermediaries (FIs)?

We try to fill this gap in the literature by providing an empirical analysis of BCs based on their financial statements, following the approach of previous studies that use balance-sheet and income-statement data to define firm profiles (Pellegrini *et al.*, 2020; De Simoni, 2022; Cariello *et al.,* 2024).

The findings of our research may help AML Functions within FIs to identify BCs more effectively and promptly. When combined with other red flags, such as those outlined by UIF (2020), our proposed approach could facilitate timely reporting to UIF, thereby mitigating both reputational risks associated with having criminals as customers while also reducing the impact of possible sanctions.

To address these research questions, we collected all rulings from the Italian Supreme Court (*Corte Suprema di Cassazione* or simply *Cassazione*) between 2018 and 2023 related to BCs, freely accessible at Sentenze Cassazione (giustizia.it),[3] along with STRs involving suspected BCs. After having selected a sample of BCs, we compared them to a group of ROCs – firms with similar structural characteristics – using the Propensity Score Matching, as well as to a sample of SCs identified from Cassazione rulings (Third Penal Section) between 2018 and 2020 (Pellegrini, 2024b).

The comparison between ROCs and BCs, conducted through regression analysis, and between SCs and BCs, performed using a Welch t-test, allowed us to confirm our hypothesis that BCs have an "amphibious" nature, sharing characteristics with both ROCs and SCs. Indeed, our results, based on the analysis of financial statements, show that during the fraud BCs have shorter payment cycles, lower working capital and higher purchase-to-revenue ratios. At the same time, similar to ROCs, they rely on bank financing to support their operations. BCs also show higher revenues per capita than both SCs and ROCs. Given these differences, we estimated a logistic regression model to discriminate between BCs and other firms. As we will show in Section 5, we used the estimated coefficients and predicted logit values from this regression to construct a composite indicator for identifying potential BCs.

[3] See https://www.italgiure.giustizia.it/sncass/ last time accessed on 23 September 2023.

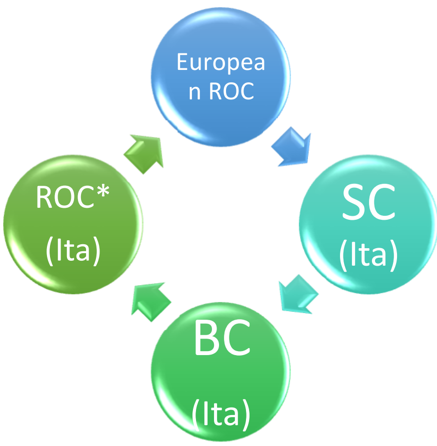
The remainder of this paper is organized as follows: in Section 2, we outline our expectations regarding the characteristics of BCs, which serve as a basis for defining the methodological approach used. In Section 3, we discuss how we built the sample and present some descriptive evidence on BCs. In Section 4, we illustrate our empirical findings. In Section 5, we introduce a composite indicator for detecting BCs. Lastly, we draw some concluding remarks in the last section.

2. Expectations on BCs characteristics

BCs operate within a complex criminal network in which they commit fiscal fraud by issuing and receiving false invoices, with the aim of making the detection of ROCs — which ultimately profit of illegal fiscal benefit — more difficult. More specifically, BCs are often positioned in the "middle" of the fraud chain, between SCs and ROCs, which is why they are referred to as "buffers" or "filters".

Figure 1 illustrates the role of BCs in the VAT fraud chain. In this example, a European ROC issues an invoice to an SC without VAT, as the transaction qualifies as an intra-community supply and purchase within the EU. The SC then invoices an Italian BC with VAT but unlawfully withholds the collected VAT instead of remitting it to the relevant tax authority. The BC issues an invoice, including VAT, to a fraudulent Italian ROC and offsets its VAT debit with its VAT credit, thereby reducing or eliminating the amount of VAT it must remit to the tax authority. The ROC claims the VAT credit for purchases from the BC and sells the goods as an intra-community supply to a European ROC, which is exempt from VAT. In summary, the SC owns a VAT debt which remains unpaid; the BC compensates VAT debt and VAT credit; the ROC claims a VAT credit from the State.

Figure 1. A network of ROCs, SC and BC in VAT fraud



Source: GdF (2017, p. 157). The asterisk (*) indicates that this Italian ROC is fraudulent, benefiting from a false VAT credit.

In this scheme, the objective is to separate the fraudulent ROC — which illegitimately claims VAT credits — from the SC, in order to conceal the connection between them. As a result, the fraud chain becomes more complex. Typically, BCs either avoid paying VAT or pay a reduced amount because the values of their issued and received invoices are similar, effectively offsetting each other.

Regarding their characteristics, BCs are expected to be "amphibious" in nature since during the fraud, which has a considerable weight in the BCs' activity, they share characteristics both with SCs and ROCs.

i) BC characteristics: resemblance to SCs and divergence from ROCs

As described in Figure 1, BCs and SCs performs a similar role in the fraud scheme by issuing and receiving false invoices at higher rates than their peers, with equivalent amounts for both. This behavior likely leaves traces in their bank accounts, where inflows and outflows happen quickly and balance out between debits and credits (GdF, 2017; UIF, 2020). Moreover, this behavior is expected to appear in their balance sheets.

Specifically, BCs are expected to have higher revenues (R) and costs (P) than ROCs and SCs because during the fraud[4]: a) their turnover includes revenues from both legitimate business (like ROCs) and fraud-related invoices (like SCs); b) their purchases of goods and services reflect both actual business needs (like ROCs) and fictitious transactions for fraud (like SCs). In addition, since costs (P) should mirror revenues (R), as described in GdF (2017, p. 157), we expect the value of $(1 - P/R)$ to be lower for BCs than for ROCs (whose aim should be to be profitable, i.e., $P<R$), and similar to SCs (which do not need to be profitable, i.e., $P \approx R$).[5]

Furthermore, BCs are expected to exhibit the following characteristics:

a) BCs have a shorter Days Inventory Outstanding (DIO),[6] which represents the average number of days in which goods remain in the inventory before being sold. This is because false invoices represent fictitious goods that do not remain in stock;

b) Since fraud-related issued invoices are cashed in immediately, BCs also have a shorter Days Sales Outstanding (DSO),[7] which measures the average number of days between the issuing of an invoice and its payment;

[4] In this work, we assume that issued and received invoices correspond, respectively, to revenues and costs pertaining to the financial year.
[5] A similar indicator to 1-P/R is in Pellegrini *et al.* (2020).
[6] Defined as $\frac{Inventory}{Revenues} * 360$.
[7] Defined as $\frac{Commercial\ credits}{Revenues * 1.22} * 360$.

c) BCs also have a shorter Days Payable Outstanding (DPO),[8] which measures the average number of days between the receiving of an invoice from providers and its payment.[9] This happens because fraud-related received invoices are paid immediately.

This behavior closely resembles that of SCs (§ 4.2.2 Comparing BCs to SCs) and it is highlighted by the UIF in the fiscal fraud red flags (pattern A, UIF 2020): "*systematic coincidence of the invoice settlement and issue date*".

The Working Capital Cycle (WCC) is calculated as the sum of Days Sales Outstanding (DSO) and Days Inventory Outstanding (DIO), minus Days Payable Outstanding (DPO), as in $\{1\}$. It measures the average number of days between the payment for resources and the receipt of money from customers. A longer WCC may indicate a liquidity issue, requiring short-term financing.

$$\{1\} \quad WCC = DSO + DIO - DPO$$

Since WCC increases with DSO and DIO, but decreases with DPO, the reduction in DSO and DIO generally leads to a shorter WCC. Although a significant decrease in DPO could offset this effect, the overall result is a likely decrease in WCC. Therefore, we expect BCs to have a WCC as short as SCs and shorter than that of their ROC peers.

It is important to highlight that days outstanding are influenced by several factors, such as a firm's market power, size, sector and unique commercial strategies[10] (Sostero *et al.*, 2021). Therefore, while BCs are likely to have smaller WCCs, a low WCC alone is insufficient to identify a firm as a BC, as many confounding factors could contribute to its reduction.

[8] Defined as $\frac{Debts\ to\ suppliers}{Purchases\ for\ goods\ and\ services * 1.22} * 360$.

[9] Some words of caution are needed: *i)* DIO, DSO, and DPO ratios compare stock data (in the numerator) with flow data (in the denominator). For this reason, it is preferable to use the average of the opening and closing balance sheet values in the numerator. Averaging smooths out timing mismatches and provides a more accurate representation of the stock level relative to the flow over the reporting period. Nevertheless, as recognized by Sostero *et al.* (2021), for external analysts, financial statement values can be used; *ii)* for DIO, DSO and DPO we used Cerved formulas; *iii)* for DSO and DPO, since credits and debits incorporate VAT, we multiplied revenues and purchases for 1.22, given that in Italy VAT at 22% is applied for most products. We could have separated debits and credits from VAT, dividing credits and debts by 1.22, but results would not change; *iv)* Cerved collects information on credits and debts composition also from the explicatory notes, whenever this information is not available from financial statements.

[10] For example, firms can pay later due to their economic power. This is especially true in Italy, where only 13% of the payments of large enterprises are made on time, compared to 53% of the payments made by micro-enterprises (European Commission 2024). Moreover, several reports highlight how Italian firms are among the worst payers in Europe (Allianz Trade, 2023; Informa, 2024). Italy has also a higher number of companies suffering from late payments compared to the European average, 52% versus a European average of 43% (European Commission 2024).

WCC is measured in days and, in order to obtain an index closely related it, we can consider the ratio between working capital (WC) and revenues (R), resulting in the working capital rate (WCR):

$$\{2\}\ \ WC = receivables + inventory - payables$$

$$\{3\}\ WCR = \frac{WC}{R}$$

where receivables stand for commercial credits with customers and payables for debts with suppliers. A BC, during the fraud, issues and receives invoices that are cashed in and paid in a very short time span. This should reduce credits, debits and stock, and since revenues (R) increases as well, WCR is expected to be smaller than that of ROCs peers and similar to SCs.[11]

As for WCC, WCR is also affected by many confounding factors like market power, sector, or company commercial policies (Sostero *et al.,* 2021).

ii) **BCs characteristics similar to ROCs (peers) and different from SCs**.

BCs are real, active companies that engage in some illicit transactions. As such, we expect them to hold tangible assets, bank debt, equity, and employ staff — characteristics they share with ROCs but not with SCs (Pellegrini *et al*., 2020). Moreover, BCs can also be large firms, meaning that their total assets might exceed those of SCs and be comparable to or even larger than those of ROCs.[12] Given that BCs are typically larger than SCs, certain financial ratios with revenues or assets as denominators may result in similar values for both SCs and BCs, despite size differences.[13]

One way to distinguish between SCs and BCs is by examining their bank exposure, using data from the Central Credit Registry (CR) managed by Bank of Italy (§ 4.2.3). Like ROCs and unlike SCs, BCs may rely on long-term bank loans to finance investments and sustaining business activity. However, for short-term financing, BCs are likely to exhibit lower exposure, such as limited used of loans backed by receivables or revolving credit lines. This is because they generally

[11] Note that, even though we suppose that credits, debits and stock reduce also for SCs, the composition of their balance sheet should remain as described in Pellegrini *et. al* (2020): SCs should have more current assets than tangible assets (which should be very low, tending to zero) and, in a specular way, more current liabilities than equity (which should be at minimum level required by the law).

[12] It is also possible that BCs and ROCs have similar assets, as false invoices do not necessarily require an increase in assets.

[13] As stated in Pellegrini *et al.* (2020, page 25), we could find false positives SCs: "*The false positives found, however, include, for example, some large manufacturing companies with very high revenues and assets that reduce the values of the variables chosen at the numerators of elementary indices*".

face fewer liquidity constraints, as fraudulent transactions are promptly paid,[14] and they may also avoid bank scrutiny of their false invoices. Therefore, long-term bank exposure is expected to be similar for ROCs and BCs, while ROCs are more likely to rely on short-term financing. In contrast, SCs are rarely visible in the credit registry or display much lower visibility compared to both BCs and ROCs.[15] Lastly, it is important to highlight that a lower need for short-time financing could lead to significant savings for BCs, in terms of lower bank interests and commissions. This may give an (unlawful) advantage to BCs over ROCs.

Eventually, while SCs are specifically created for the purpose of fraud and consistently act illegally, BCs may only take part in the criminal network for a limited period of time. Therefore, it is assumed that outside the years of offense, BCs operate like regular ROCs.

Table 1 provides a summary of all these considerations.

Table 1. Summary of expectations on BCs characteristics. Comparison between BCs and SCs and between BCs and ROCs.

Index and values	BCs vs SCs	BCs vs ROCs
Revenues (R)	>	>
Purchases (P)	>	>
Assets	>	>=
1-P/R	=	<
Days Outstanding (DSO/DIO/DPO)	=	<
Working Capital Cycle (WCC)	=	<
Working Capital Ratio (WCR)	=	<
Bank Debt (CR)	>	<=

3. Background and data

This section provides information about the construction of our sample of BCs (3.1 *The sample of BCs*) and then presents some descriptive statistics (3.2. *Descriptive evidence*).

3.1 The sample of BCs

To assemble a sample of BCs we rely on two main sources: *i)* rulings of the Supreme Court (*Cassazione*) and *ii)* STRs database of the UIF. Overall, we identify 92 firms considered BCs. More specifically:

[14] Note that incoming payments related to false invoices could create a liquidity buffer, which could also be used for the payment of legitimate invoices received for real operations.

[15] Note that if we use a ratio such as bank debt over total liabilities, and the denominator is very large—as expected—we might find that BCs have values not statistically different from SCs, even though BCs have bank debt and SCs do not.

i) From the *Cassazione* database, we selected all rulings containing keywords that may be related to BCs from 2018 to September 2023. We analyzed each of them[16] and selected 78 firms involved in those rulings as BCs. We considered both civil and criminal offenses. In the Italian system, after the first appeal, defendants can bring their case to the *Cassazione,* whose rulings from the last 5 years are published online. The rulings include an explanation of the cases' history and the motivation behind the sentences. Most rulings confirm the decision of the court of appeal. In a minority of cases, the *Cassazione* overturns the decision. We also included BCs from overturned rulings for two main reasons. First, the ruling does not directly involve the BCs, but rather the owners or managers of the ROCs which benefitted from the BCs; for this reason, we were not able to assess if the BCs joined the fraud because of unfaithful managers or with the knowledge of the owners. Second, the *Cassazione* typically does not overrule the interpretation of the lower court, but it rules on violations of the defendants' rights or procedural errors of the lower courts (for this reason the role of *Cassazione* is also called "trial of the trial"). Thus, even if a case is overruled, the existence of the fraud is not questioned. This dataset is particularly appealing because, in most rulings, there are references to the specific years in which the fraud was perpetrated (hereinafter we refer to those years, when available, as years of tax assessment or years of assessment);

ii) The STRs database contains all reports submitted to the UIF from obliged entities (mostly FIs) reporting suspicious activity that may be related to money laundering. In theory, when FIs observe a tax fraud scheme involving SCs or BCs, they should file a report with the UIF. We extracted all STRs containing keywords related to BCs from 2013 to September 2023 and, after reviewing them, we identified the names of potential BCs. Overall, despite nearly 7,500 STRs filed each year related to tax fraud involving false invoicing, we identified only 14 firms that appear to have acted as BCs. This raises concerns about how the role of BCs is still under-recognized or not easily identifiable by entities subject to AML obligations.

By reviewing the court rulings and STRs, in most cases we were able to identify with certainty the years in which the fraud was perpetrated. Out of the 92 firms identified, we successfully determined the relevant assessment years — i.e., the years in which the fraud allegedly occurred — for 69 firms. We then merged these firms with financial statement data from the Cerved dataset, which includes data on the universe of Italian non-financial corporations. Cerved collects firm-level data on Italian limited liability and joint-stock companies that are required to report their financial statement data each year. The dataset standardizes this information to ensure

[16] Keywords refer to the different names to which BCs are usually referred to in Italian: *filtro, cuscinetto and buffer*.

comparability across firms and includes data on revenues, assets, costs, liquidity along with major structural characteristics (sector, localization, legal form). Unfortunately, only 39 of the 69 firms reported at least one financial statement between 2002 and 2022, which defines the final size of our sample.

Figure 2 shows that the last year in which each BC was subject to tax assessment by LEAs ranges from 2004 to 2021. Regarding the behavior of BCs, we can be confident that these companies engaged in illicit activity during the years in which they were under assessment. However, we could not determine whether fraud occurred in the years prior to the assessment and — as shown in Section 4.4 (Dynamics) — whether, after the assessment, these firms modified their behavior, possibly ceasing to act as BCs and returning to lawful ROC status, as hypothesized in Section 2. Therefore, we adopted a conservative approach: we excluded all years before and after the period of known fraudulent activity, since we had no reliable information about the firms' behavior during those times.

Figure 2. Distribution of BCs by year of tax assessment

3.2. Descriptive evidence

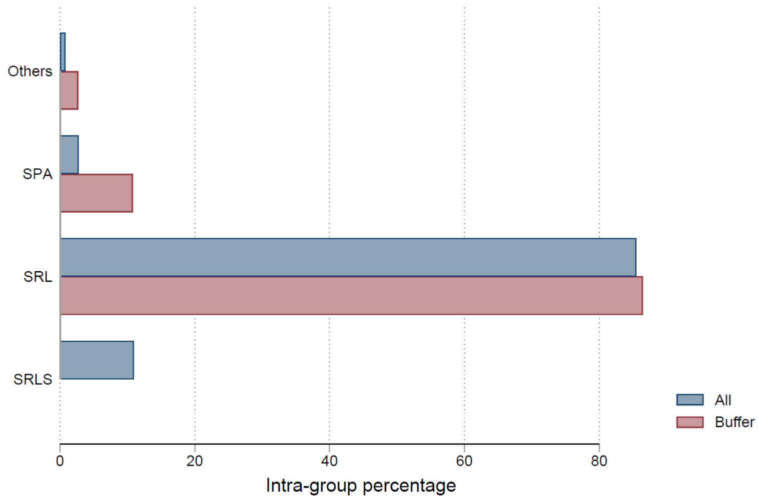
In this section, we present some descriptive evidence on the main structural characteristics of BCs, including their legal form, economic sector and size, in order to highlight how they differ from the overall population of Italian firms.

Before comparing the two groups of firms, we transformed our panel dataset into a cross-sectional one by collapsing the data at the firm level and computing the average of all financial variables and ratios over the observed years. For BCs, these averages are calculated exclusively over the years for which a tax assessment was carried out, since, as we will explain in the sequel, only for those years we can confidently identify them as BCs. In contrast, for the population of

Italian firms, we considered all years for which financial statements are available. For the structural characteristics expressed as categorical variables, such as legal form and economic sector, we determined the modal category for each firm. We adopted this cross-sectional approach to account for the varying number of yearly observations per firm, which could otherwise introduce a bias due to differences in firm age, performance, or sample coverage.

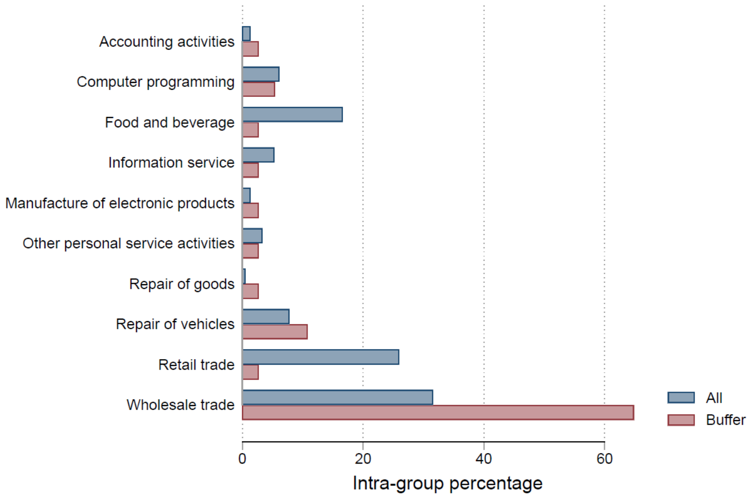
Legal form distribution. An examination of the legal status distribution in our sample reveals a relative higher concentration of joint-stock companies (SPA, "*Società per Azioni*", in the figure) among BCs compared to the broader population of industrial companies registered in the Cerved database. Notably, the BCs sample does not contain any instances of simplified limited liabilities companies (*SRLS*), which represent a less complex form of limited liability companies (*SRL*). In contrast, the proportion of limited liability companies (SRL) is similar across both samples (figure 3).

Figure 3. Distribution of BCs and all Italian firms by legal form



Sectoral distribution. As shown in figure 4, the majority of BCs operate in the wholesale trade sector, which frequently involves transactions with foreign entities. This sectoral concentration aligns with patterns observed in fraudulent activities, as trade, particularly international trade, can facilitate schemes such as the generation of false invoices, including VAT fraud.

Figure 4. Distribution of BCs and all firms by sector



Dimensional distribution. From a dimensional perspective, BCs display notable differences relative to the overall population of Italian firms. While more than 80% of Italian companies are classified as micro-enterprises, less than half of the firms in the BC sample fall in this category. This suggests that BCs tend to be relatively larger companies compared to the general population of Italian firms (figure 5).[17]

Figure 5. Distribution of BCs and all Italian firms by size

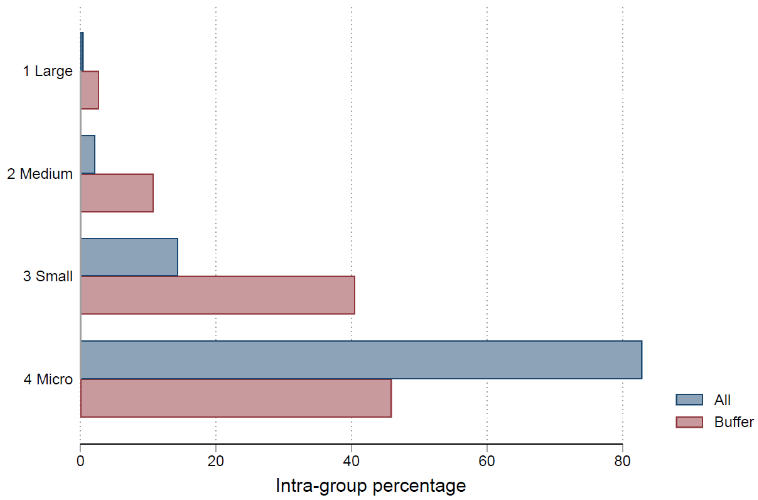


Table 2 compares the average number of employees, revenues, and assets values (all expressed in logarithmic form) between the entire population of Italian firms and the sample of BCs. The table also reports results of Welch's t-test assessing the statistical significance of the observed differences. The results indicate that the BCs have significantly higher revenues and

[17] Micro firms have assets less or equal than 2 million of euro. Small firms have assets between 2 and 10 million. Medium firms have assets between 10 and 43 million. Large firms have assets larger than 43 million.

assets than the average Italian firm. However, no significant difference emerges in terms of the number of employees.

Table 2. Differences in means (Welch t test) between BCs and all Italian firms

	(1) All corporations - all years (A)	(2) Buffer companies - years of tax assessment (B)	(3) (B) - (A)
Employees, log	1.139	1.476	0.336
Revenues, log	5.653	9.286	3.633***
Assets, log	5.841	7.848	2.007***
Obs.	1,595,023	39	

Notes: This table represents the main characteristics between BCs companies in the years of tax assessment and all Italian corporations and BCs. All data are collapsed at firm-level.

Overall, the descriptive evidence presented so far suggests that direct comparison between BCs and the entire population of Italian non-financial firms may be misleading, as substantial differences in structural characteristics, such as sector of activity and size, cannot be overlooked. To appropriately address these differences, the following section outlines our empirical strategy which employs a statistical matching procedure to build a control sample of lawful firms sharing similar characteristics with BCs.[18]

4. BCs behavior: evidence

4.1 The selection of the control sample

As highlighted in the descriptive evidence section, BCs are disproportionately represented in the trade sector, and a noteworthy proportion of them are joint-stock companies. To ensure an appropriate comparison with lawful firms, we selected a control sample that accurately reflects these characteristics. To this end, we employed a Propensity Score Matching (PSM) strategy.

PSM is a statistical matching technique designed to estimate treatment effects by accounting for structural characteristics that may influence the likelihood of being assigned to the treatment group. In particular, the propensity score represents the conditional probability of assignment to treatment (in this case, the BC status) given a set of observed variables (Rosenbaum and Rubin, 1983; Leuven and Sianesi, 2003). This technique offers several advantages, including

[18] With respect to regional distribution, our analysis does not identify any noteworthy or systematic patterns.

the reduction of the dimensional matching problem to a single dimension (the propensity score). As we will show in the following section, PSM more effectively replicates the structural characteristics of the treatment group in the control sample. Thus, PSM allows us to mitigate the effect of the over-representation of wholesale trade firms in the sample of BCs. At the same time, given its statistical nature, PSM allows units with dissimilar structural characteristics to be selected, if they share a similar propensity score. The primary objective of this matching procedure is to minimize heterogeneity in observable characteristics (such as localization, sector of activity and firm age), thereby reducing the influence of confounding factors related to omitted variables. For instance, given that most BCs operate in the trade sector, it is crucial that the control group is similarly distributed across this sector. As long as PSM provides a credible counterfactual (based on observables structural characteristics) for non BCs, any differences in financial statement variables can be more plausibly interpreted as exogenous, rather than arising from an endogenous selection bias.

From an operational point of view, our PSM procedure accounts for geographic factors at the provincial level, sector of activity using 2-digit Ateco codes, decade of establishment as a proxy of firm age, and legal form. For firm size, we classify firms into three categories based on the 25th and the 75th percentiles of the distribution of revenues of the BCs (4,4 million of euro and 36,3 million of euro, respectively). By matching on these variables, we are reasonably confident that our procedure effectively controls for observable structural characteristics that could influence financial statements. Although we cannot claim that the only difference between the two samples is the BC status, this approach brings us substantially closer to that ideal scenario. Our PSM sample is our counterfactual and we argue that firms in the control group are not BCs, even if some of them may be, and they represent ROCs. We refer to the PSM sample as the ROCs sample.

We assess post-matching balance across all covariates included in the matching procedure to ensure the validity of our results. Further details on the post-matching analysis are provided in the Appendix.

4.2 Empirical evidence

This section presents the core of our empirical analysis, which involves estimating a series of regressions on key variables coming from firms' financial statements to assess whether BCs exhibit significant differences from their peers. Peer firms are identified using a PSM approach, as described in Section 4.1. In Section 4.2.1 and 4.2.2, we conduct direct comparison of BCs with

ROCs and SCs, respectively, focusing on several financial variables and ratios. Section 4.2.3 BCs bank exposureinvestigates how bank exposure varies across these types of firms.

4.2.1 Comparing BCs to ROCs

The comparison with BCs and their ROCs peers is carried out using the following linear regression:

$$\{4\}\ y_i = \alpha_i + \beta_1 \times \text{Buffer}_i + \boldsymbol{\beta}_2 \times \text{FE}_i + \varepsilon_i$$

The dependent variable represents a financial variable or ratio derived from firms' balance sheets. The main explicative variable, *Buffer*, is a dummy that takes the value of 1 if the firm belongs to the BCs sample and 0 otherwise. FE denotes a set of fixed effects included to account for structural characteristics, namely industry, province, size class, and cohort of birth. Our primary parameter of interest is β_1 , which captures the differential effect for BCs relative to their matched peers.

Table 3 and Table 4 summarize the differences in the financial statement indicators between these two groups. Table 3 focuses on measures of size, profitability, and productivity. The results indicate that, despite operating with fewer production factors, namely a lower number of employees, BCs generate higher revenues than their peers. When considering profitability, the two groups show similar outcomes when measured by the EBITDA-to-revenue ratio, while BCs exhibit slightly lower profitability when measured by the value added-to-revenue ratio. In contrast, BCs outperform their peers in terms of productivity, as evidenced by higher revenue per employee.

Table 4 shows that Days Sales Outstanding (DSO), Days Inventory Outstanding (DIO), and Days Payable Outstanding (DPO) are all significantly lower for BCs. This is likely attributable to the fact that invoices related to the fraud are settled promptly, thereby reducing both commercial credits and debts. Additionally, BCs may use liquidity obtained from the fraud to settle genuine invoices. These factors contribute to a shorter working capital cycle and result in lower working capital ratios. In this type of fraud, increases in revenues are offset by corresponding increases in costs. This pattern is reflected in the significantly higher level of net purchases and higher net purchases-to-revenues ratio observed for BCs.

Table 3. Dimension, profitability and productivity

	(1) Employees, log	(2) Revenues, log	(3) Assets, log	(4) EBITDA over rev.	(5) VA over revenues	(6) Revenues per capita
Buffer	-0.452**	1.129***	-0.0379	0.0163	-0.0449*	388.3***
	(0.195)	(0.170)	(0.222)	(0.0157)	(0.0238)	(64.85)
Observations	384	398	398	398	398	384
R-squared	0.461	0.741	0.695	0.130	0.320	0.586
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Size class FE	Yes	Yes	Yes	Yes	Yes	Yes
Legal form FE	Yes	Yes	Yes	Yes	Yes	Yes
YOB cohort FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Buffer is a dummy variable that takes value 1 in the years of tax assessment of the buffer companies and 0 for other firms. All data are collapsed at firm-level. To select the control group we apply a propensity score matching procedure. All regressions include 2-digit industry, province, size class, legal form and cohort of birth fixed effects. Standard errors are clustered at the firm level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 4. Liquidity cycle and purchases

	(1) DSO	(2) DPO	(3) DIO	(4) Working capital cycle	(5) Working capital rate	(6) Purchases over rev.	(7) Purchases, log
Buffer	-43.89***	-42.76***	-32.04***	-32.94***	-0.164***	0.164***	1.754***
	(8.122)	(10.62)	(10.99)	(10.89)	(0.0337)	(0.0298)	(0.253)
Observations	398	398	398	398	398	398	398
R-squared	0.232	0.220	0.136	0.159	0.232	0.437	0.701
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Size class FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Legal form FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YOB cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Buffer is a dummy variable that takes value 1 in the years of tax assessment of the buffer companies and 0 for other firms. All data are collapsed at firm-level. To select the control group we apply a propensity score matching procedure. All regressions include 2-digit industry, province, size class, legal form and cohort of birth fixed effects. Standard errors are clustered at the firm level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

The results obtained are consistent with our expectations:

i) BCs are comparable to ROCs in terms of total assets, but employ fewer personnel while reporting higher revenues and costs. This finding aligns with the theory of false invoicing, which posits that both sales and purchases are artificially inflated through fictitious transactions. The fraudulent nature of these activities implies such increases do not necessitate a scale-up in actual operations;

ii) BCs exhibit fewer days outstanding, shorter WCC, smaller WCR, and larger purchases.

4.2.2 Comparing BCs to SCs

Drawing on the dataset assembled by Pellegrini (2024a), which comprises a sample of SCs from the Third Criminal Section of Cassazione in the period 2018–2020, we build a list of 31 SCs that disclosed at least one financial statement between 2002 and 2022.[19] For the purposes of comparative analysis, we perform a Welch t-test to assess differences between BCs and SCs for which financial statements are available.

Table 5 reports the differences in mean values between our sample of BCs and the sample of SCs. SCs systematically report lower values across all main economic dimensions, including employment, revenues, purchases, and total assets. Consistently with our expectations, we find no statistically significant differences between the two samples with respect to Days Inventory Outstanding (DIO), Days Sales Outstanding (DSO), Days Payables Outstanding (DPO), Working Capital Cycle (WCC), and Working Capital Ratio (WCR). However, revenues per employee are significantly larger for BCs.

Table 5. Differences in means (Welch t test) between BCs and SCs.

	(1) Shell Companies - all years (A)	(2) Buffer companies - years of tax assessment (B)	(3) (B) - (A)
Employees, log	0.711	1.476	0.765*
Revenues, log	7.730	9.286	1.556***
Assets, log	6.977	7.848	0.871*
EBITDA over revenues	0.039	-0.042	-0.003
Revenues per capita	789.999	1051.554	261.556*
VA over revenues	0.104	0.092	-0.012
Days sales outstanding	57.473	47.085	-10.388
Days payable outstanding	82.811	60.193	-22.618
Days inventory outstanding	45.833	28.044	-17.789
Working capital cycle	25.732	35.171	-9.439
Working capital rate	0.159	0.134	-0.025
Purchases over revenues	0.689	0.796	0.107
Purchases, log	7.138	9.010	1.872***
Obs.	31	39	

Notes: This table represents the main characteristics between BCs companies in the years of tax assessment and a sample of SCs. All data are collapsed at firm-level.

[19] Source: Cerved.

4.2.3 BCs bank exposure

From the aforesaid results, we note that, despite observing some differences between SCs and ROCs, we cannot distinguish BCs from SCs by looking only at their financial statement variables and indicators. Nevertheless, as outlined in Section 2, we can possibly argue that SCs are reluctant to rely on the banking channel. To test this hypothesis, we examine the data. Specifically, we leverage the Italian CR, a loan exposure database that records all firm-bank credit relationships in Italy. The CR data exclude loans below euro 75,000 before 2009 and loans below euro 30,000 after 2009. Data are available at a monthly frequency and are of very high quality, since financial intermediaries use the CR as a screening and monitoring device for borrowers. In simplified terms, we can say that loans are classified into three main classes: revolving credit lines, term loans, and loans backed by accounts receivable. The dataset includes both granted and drawn amounts. We focus on drawn credit, as it better captures the borrower's decision to use available credit lines — a choice largely driven by demand-side factors. In contrast, granted credit is primarily influenced by supply-side decisions made by banks.

In terms of bank exposure, 35% of SCs were recorded in CR between 2002 and 2022, compared to 69% of BCs, a figure broadly in line with the ROC sample (75%). Presence of companies in CR can be represented as a binary variable: 1 if a company is listed in CR and 0 if it is not. This variable is a particularly useful tool because it is readily available to FIs such as banks. As just said, SCs are less frequently recorded in CR compared to BCs and ROCs. Therefore, the presence in CR could serve as a useful tool for identifying BCs. As discussed earlier, BCs exhibit fewer liquidity problems. Moreover, it is reasonable to assume that during fraudulent activities they avoid bank scrutiny of their false invoices. Consequently, BCs likely rely less on short-term financing, such as loans backed by accounts receivable or revolving credit lines, compared to ROCs. On the contrary, if ROCs behave as average Italian companies, which tend to be slow in paying, they need to edge against the liquidity gap they incur by borrowing the money they expect to receive from banks. The evidence collected in Table 6 supports these assumptions: loans backed by receivables and revolving credit lines, two instruments typically used to obtain short-term liquidity, are less common for BCs than for ROCs. Term loans, generally used for investments, show no statistically significant difference between BCs and ROCs.

Table 6. BCs bank exposure vs ROCs sample

	(1) Term loans over revenues	(2) Loans backed by receivables over revenues	(3) Revolving credit lines over revenues
Buffer	-0.0952	-0.0353**	-0.0279**
	(0.132)	(0.0140)	(0.0119)
Observations	219	219	219
R-squared	0.233	0.210	0.226
Industry FE	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Size class FE	Yes	Yes	Yes
Legal form FE	Yes	Yes	Yes
YOB cohort FE	Yes	Yes	Yes

Notes: Buffer is a dummy variable that takes value 1 in the years of tax assessment of the buffer companies and 0 for other firms. All data are collapsed at firm-level. To select the control group we apply a propensity score matching procedure. All regressions include 2-digit industry, province, size class, legal form and cohort of birth fixed effects. Standard errors are clustered at the firm level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

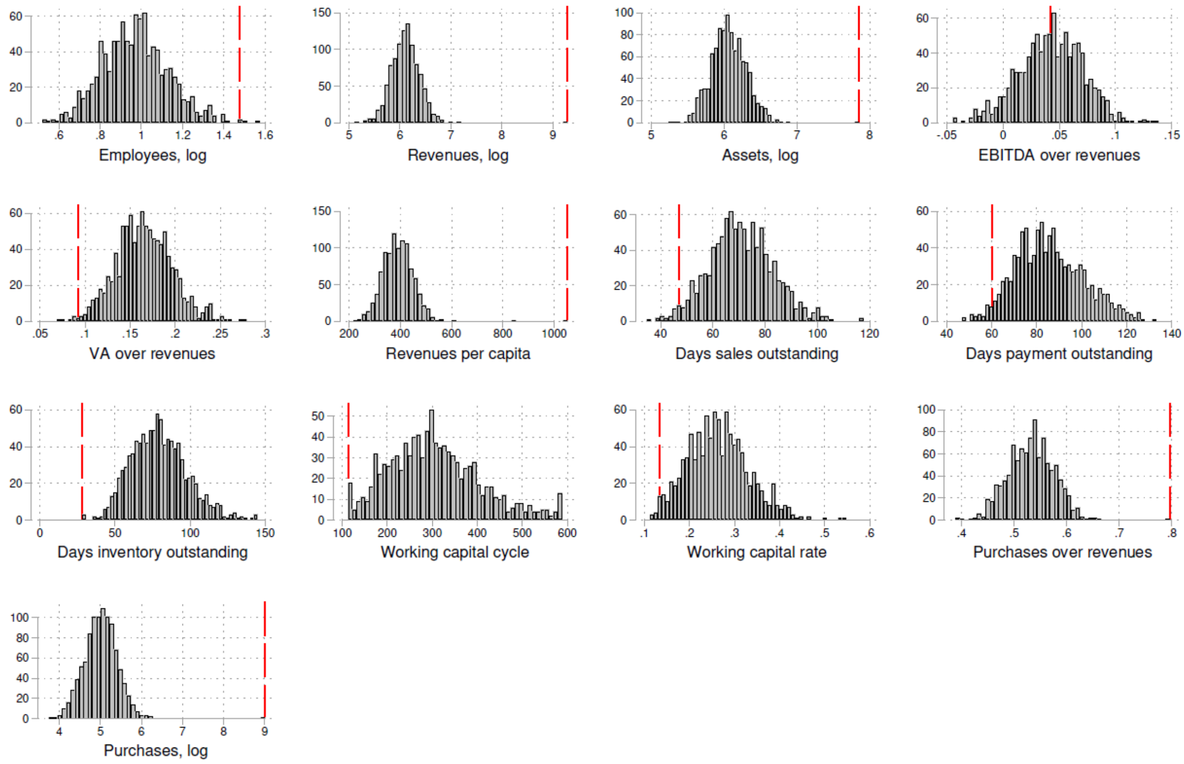
4.3 Robustness analysis

We assessed the significance of our estimates by addressing whether our results could be entirely driven by chance. Following a variation of the falsification test proposed by Abadie *et al.* (2010) and Pinotti (2015), we tested the null hypothesis that being a BC does not affect financial statement variables. This null hypothesis can be rejected if the effect estimated for the 'true' treated units (i.e., the BCs) is abnormal relative to the distribution of placebo estimates. To validate our findings, we conducted a similar test by calculating the averages of selected financial statement variables across 1,000 random samples of 39 firms each, selected to resemble BCs in key characteristics (with at least 10% being joint-stock companies and 80% operating in wholesale trade). This procedure might allow us to reject the hypothesis that selecting any 39 Italian firms with similar characteristics would produce the same differences in financial statement variables.

The histograms in Figure 6 show the distribution of estimates for 1,000 iterations across several financial statement variables. No placebo unit experiences a change comparable to those observed in BCs (in absolute value); thus the p-value for rejecting the null hypothesis of no treatment effect is effectively zero (Abadie *et al.*, 2010). Overall, the changes in economic outcomes observed in treated firms (BCs) during exposure (fraud) are extremely unlikely (based on the distribution of placebo estimates) under the null hypothesis of no effect on the financial outcomes. Therefore, we reject the hypothesis that we are dealing with a random sample of 39 Italian firms, even when controlling for sector and size distribution.

All graphs in Figure 6 confirm our findings (see results in tables 3 and 4), except those related to employees and assets. This result validates the use of our PSM methodology, as matching on size generates a sample of comparable firms.

Figure 6. Distribution of selected variables from 1,000 stratified random samples of Italian firms



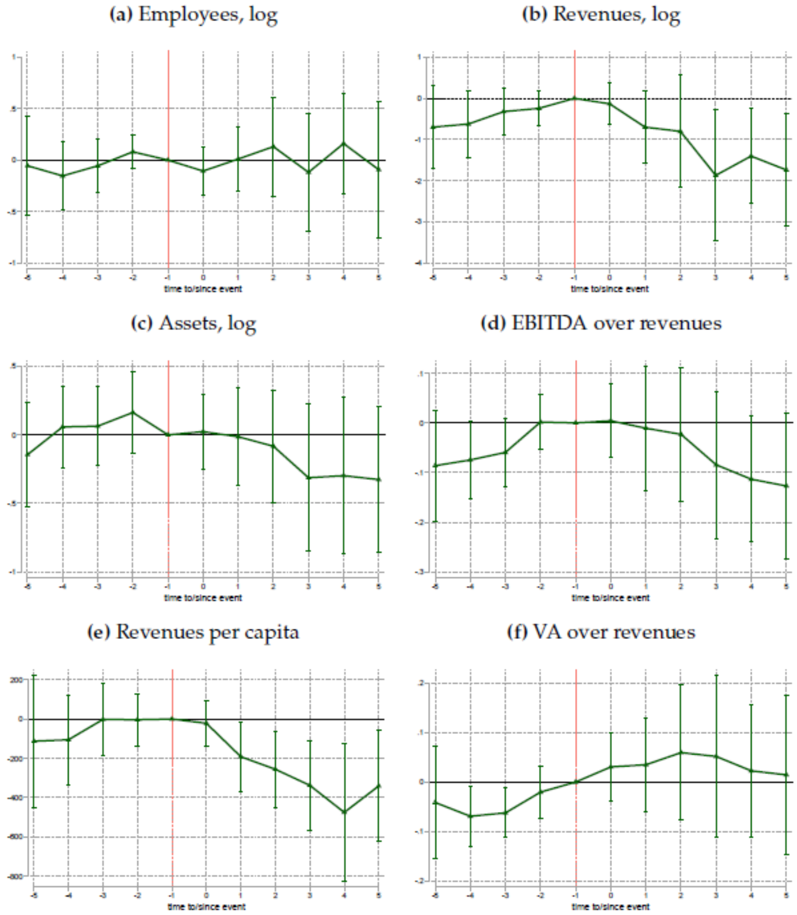
Note: the dotted red line represents the average value for the BCs.

4.4 Dynamics: BCs after assessment

Finally, we compared the outcomes of BCs after the final year of fraud relative to those of a suitably constructed comparison group of non-BCs, using a pseudo difference-in-differences framework to determine if, after they have been caught, BCs changed their behavior.

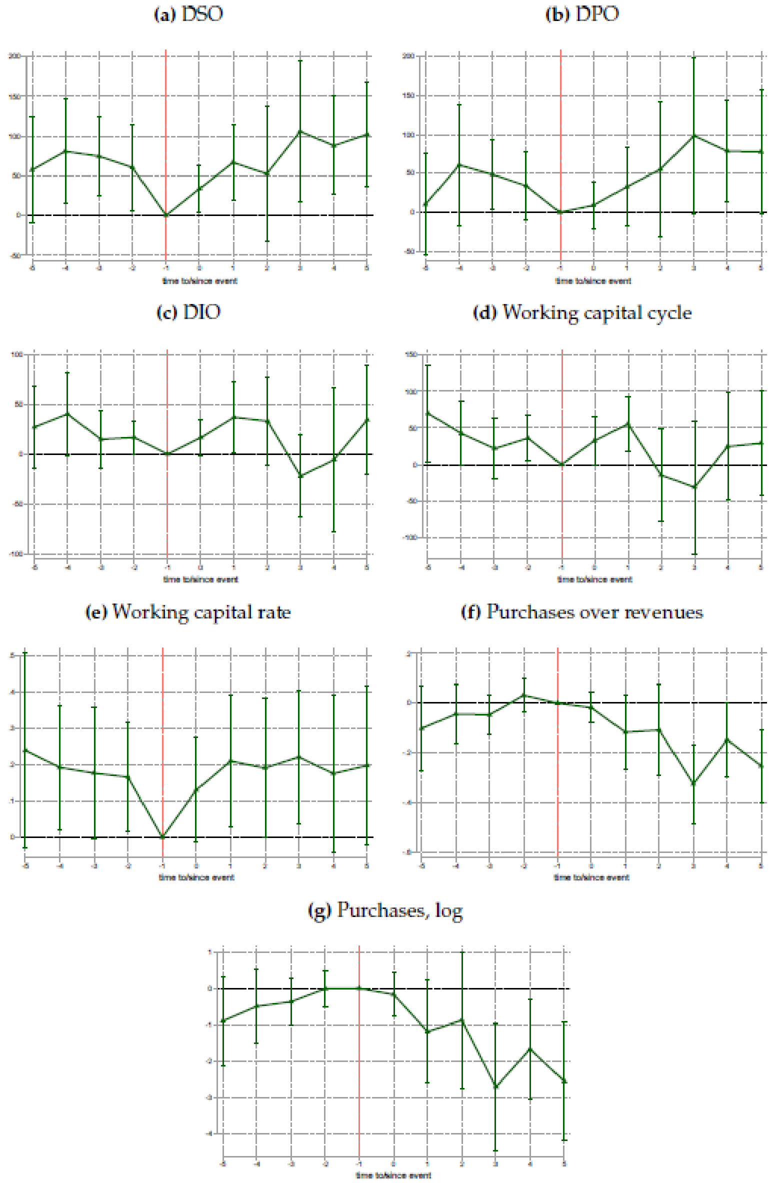
Interestingly, following the final year of investigation, factors of production are stable, while revenues and purchases decline. Productivity (VA/R) remains stable, and the purchases-to-revenues ratio decreases. DSO, DIO and DPO increase, along with WCC and WCR. This evidence is consistent with the hypothesis that, after being detected, BCs revert to normal operations and they thus experience a sort of reversion to the mean in comparison to the fraud years and to other firms. This finding confirms that excluding post-assessment years from the analysis was likely the correct choice.

Figure 7. Size, profitability and productivity after tax assessment



Notes: Point estimates and 95% confidence intervals. For all treated firms (BCs) we include observations from -5 and +5 years after the last year of tax assessment. The specification includes sector-year and province-year fixed effects.

Figure 8. Purchases, days outstanding and working capital rate after tax assessment



Notes: Point estimates and 95% confidence intervals. For all treated firms (BCs) we include observations from -5 and +5 years after the last year of tax assessment. The specification includes sector-year and province-year fixed effects.

5. A composite indicator to detect BCs

The analysis outlined in the previous sections reveals that BCs exhibit an "amphibious" nature, sharing characteristics with both SCs and ROCs. In particular, during fraudulent activities, BCs, like SCs, tend to have a low value-added profile, a low working capital ratio and a rapid working capital cycle. Conversely, in alignment with ROCs, BCs rely on banking channels for financing. Additionally, BCs exhibit higher productivity, measured as revenues per employee, exceeding that of both ROCs and SCs.

In this section, we leverage our empirical findings to develop a composite indicator for detecting BCs. Our approach involves estimating a logistic regression model, as detailed in the following equation:

$$\{5\}\ logit(p_i) = \alpha_i + \beta_1 \times \left(1 - \frac{P}{R}\right) + \beta_2 \times WCR + \beta_3 \times (1 - CR) + \beta_4 \times \frac{R}{E} + \varepsilon_i$$

where the response variable is a binary indicator which equals 1 if the firm is identified as a BC, and 0 otherwise, p_i is the probability that the response variable is 1 (i.e., the firm is a BC), and the right part of the equation is a linear combination of the four most relevant red flags for BC involvement in fraudulent schemes. In particular, these red flags are:

i) 1-P/R: during fraud, purchases (P) tend to be high and close to revenues (R). A value of 1-P/R close to zero increases the likelihood of identifying a BC;

ii) WCR (working capital ratio): this can be negative (less frequently[20]) or positive (more frequently). During fraud, working capital (WC) decreases and revenues (R) increase, causing WCR to approach zero. A small WCR may signal the presence of a BC, while a large value indicates otherwise;

iii) 1-CR (Credit Registry): this indicator equals 0 if the firm is listed in the credit registry and 1 if it is not. It helps distinguish BCs from SCs, as SCs typically avoid financial markets and bank scrutiny due to the lack of need for external financing;

iv) R/E (revenue per employee): this productivity measure is usually higher in BCs compared to ROCs and SCs, as evidenced in previous sections.

The results of the estimation of the logistic regression are presented in Table 7.

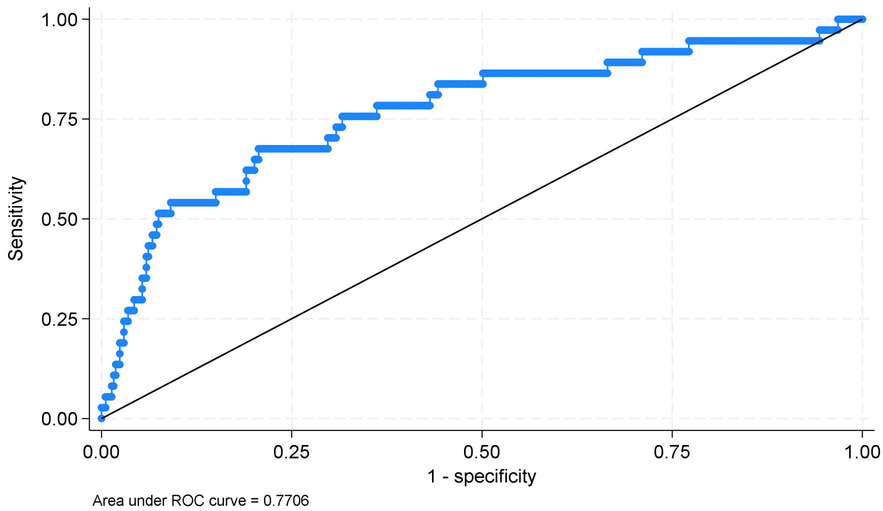
Table 7. Outcome of the logistic regression

	(1) Buffer
1 - P/R	-0.662 (1.173)
WCR	-3.259** (1.482)
1 - being in CR	0.289 (0.391)
R/E	1.299** (0.546)
Costant	-2.867*** (0.793)
Observations	410
Pseudo R-squared	0.119

[20] Overall, we find a negative value of WCR in about 20% of cases.

Logistic Regression is a classification technique designed to identify a hyperplane in n-dimensional space or a line in two dimensions that best separates firm categories, in our case BCs from other firms. From the estimation of the logistic regression model, we obtain predicted logit values. By comparing these values with a predetermined threshold, we can classify the firms: if the predicted value exceeds the threshold, the model classifies the firm as a BC; otherwise, it classifies it as a non-BC. As the threshold varies, the model will classify a greater or lesser number of firms as BCs. Each threshold corresponds to two performance metrics: specificity, which measures the proportion of non-BCs correctly identified by the model, and sensitivity, which measures the proportion of BCs correctly classified by the model. Figure 9 presents the Receiver Operating Characteristic curve (ROC curve), illustrating the relationship between sensitivity (true positive rate) and 1 – specificity (false positive rate) as the threshold varies. The area under the ROC curve is 0.7706.

Figure 9. ROC curve



Since our goal is to achieve a sensitivity of at least 75% (i.e., correctly classifying three-quarters of BCs), we select a threshold associated with a sensitivity of 75.68% and a specificity of 68.36%, corresponding to a threshold value of -2.2. Firms with a predicted logit value below this threshold are classified as non-BCs, while firms above this cut-off are classified as BCs.

Finally, we can use the logistic regression coefficients (shown in Table 7) to build a classification rule for firms. The construction of this rule involves two steps. First, we input the coefficient values into equation {5} to compute a numerical value representing the Buffer Companies Composite Indicator (BCCI):

$$\{6\}\ BCCI = -2.9 - 0.7 \times \left(1 - \frac{P}{R}\right) - 3.3 \times WCR + 0.3 \times (1 - CR) + 1.3 \times \frac{R}{E}$$

The second step involves comparing the BCCI to the threshold selected from the ROC curve, which is -2.2:

$$\{7\}\ BCCI\begin{cases} > -2.2 & we\ flag\ the\ firm\ as\ BC \\ \leq -2.2 & we\ flag\ the\ firm\ as\ NOT\ a\ BC \end{cases}$$

The BCCI serves as an initial screening tool for detecting BCs. If the indicator signals the potential presence of a BC, then it is advisable to use additional financial information to substantiate this suspicion. In particular, the analysis of Days Inventory Outstanding (DIO), Days Sales Outstanding (DSO), Days Payable Outstanding (DPO), and Working Capital Cycle (WCC) is recommended. Table 8 summarizes how red flags are expected to behave for BCs, compared to ROCs and SCs.

Table 8. Behaviour of Financial Red Flags for BC compared to ROC and SC.

	1-P/R	WCR	1-CR	R/E	BCCI	DSO/DPO/DIO, WCC
BCs	Lower than ROCs Like SCs	Lower than ROCs Like SCs	Tending to 0 Like ROCs Lower than SCs	Higher than ROCs and SCs	Larger than -2.2	Lower than ROCs Like SCs
ROCs	Higher than BCs	Higher than BCs	Tending to 0 Like BCs	Lower than BCs	Lower than -2.2	Higher than BCs
SCs	Like BCs	Like BCs	Tending to 1 Higher than BCs	Lower than BCs	Lower than -2.2	Like BCs

To support the AML function of a FI, we suggest using the BCCI alongside other methods. For instance, focusing on the variables defined in Tables 3, 4, 5 and 6 may provide additional useful red flags. It could also be beneficial to analyze whether any customers or suppliers of the firm might be a candidate SCs, as BCs and SCs often participate in the same fiscal fraud. In this regard, we recommend applying the indicators outlined in UIF (2020) and in Pellegrini *et al.* (2020).

6. Conclusion

Fiscal fraud, despite being highly detrimental to society, is often not perceived as such. This misperception, combined with the low risk it entails both in terms of penalties and public awareness, makes this kind of fraud particularly appealing to criminals. While its importance is well acknowledged by law enforcement agencies and judicial authorities, relatively few scholars have examined the firms involved in fraudulent schemes. This work aims to fill this gap by deeply analyzing the characteristics of a specific type of company often employed in the most complex fiscal fraud schemes: the so-called Buffer Company (BC).

To achieve this, we constructed an original and unique sample of BCs using rulings of the Italian Supreme Court (*Corte di Cassazione)* and data from Suspicious Transactions Reports submitted to the Italian Financial Intelligence Unit. Through these sources, we identified 92 firms with documented involvement as BCs in fraudulent schemes. For 39 of these firms, we were able to precisely identify the years in which they participated in fraud and analyze their corresponding financial statements.

We addressed potential limitations of our sample in several ways. First, we compared these BCs to a sample of firms with similar structural characteristics, such as size, sector of activity and geographical location, to control for confounding factors. Second, we compared them to multiple random samples of Italian firms to rule out the possibility that our results were driven by chance.

Our analysis enabled us to outline a typical profile of BCs. Notably, their purchases tend to increase faster than their revenues, resulting in a higher purchase-to-revenue ratio compared to ROCs, and similar to that of SCs. The use of false invoices, which are paid almost instantaneously, significantly reduces BC's Days Sales Outstanding (DSO), Days Inventory Outstanding (DIO), Days Payable Outstanding (DPO), Working Capital Cycle (WCC), and Working Capital Ratio (WCR). This is notable in the Italian context, where payment delays are common and firms often rely on bank financing to address their liquidity gaps. We also found that BCs tend to rely less on short-term financing compared to ROCs, as they face fewer liquidity constraints and they gain an unlawful advantage in terms of interests and commissions with respect to their peers. Moreover, revenue per employee is higher in BCs than in both SCs and ROCs.

We further examined the dynamics of BCs following tax assessments. We observed a sharp decline in revenues and purchases, along with an increase in payment delays, as reflected by rising DSO, DIO and DPO. This result suggests that BCs tend to revert to behaving like ROCs once their fraudulent activities are uncovered.

Based on the empirical analysis, we propose a preliminary indicator to support the AML functions of financial intermediaries in the identification of BCs within their customer base. The proposed indicator, derived from a logistic regression model, should be used in conjunction with liquidity indicators, such as DSO, DPO, DIO and WCC. Obviously, a second-level analysis is necessary to discard false positives. An additional layer of analysis (e.g., examining the characteristics of a firm's customers and suppliers) may further enhance the correct identification of BCs.

Overall, this study aims to address a gap in the literature by providing practical tools for FIs to detect and report BCs to the Financial Intelligence Unit in a timely manner, thereby mitigating potential financial and reputational risks. Nevertheless, we acknowledge that this is a preliminary pilot study and not exhaustive; additional data and analyses are needed to validate the proposed indicator.

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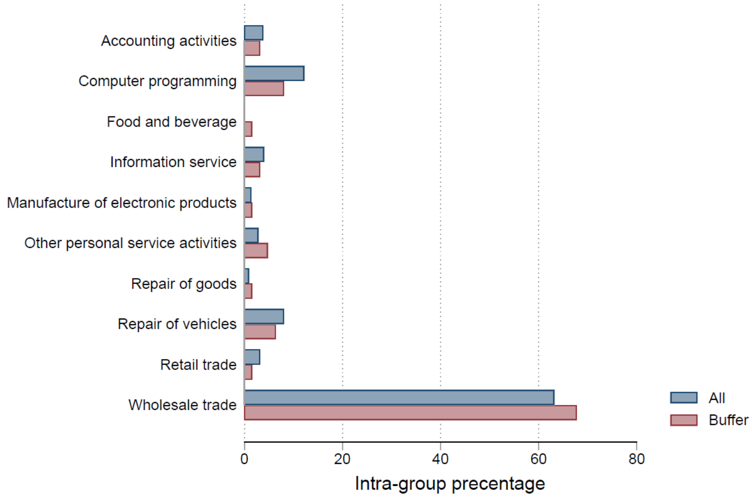
Appendix

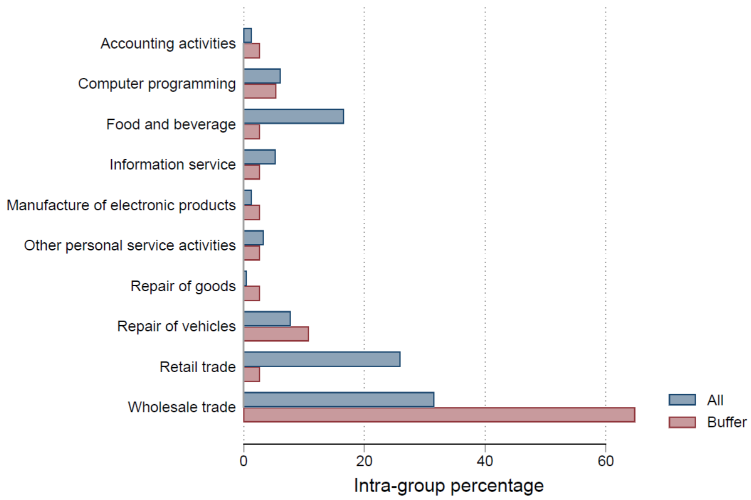
The following charts show how the PSM approach allows us to select a control group that does not differ on the structural and observable characteristics of BCs. In Figure A1 we can see that the proportion of BCs and other firms in wholesale sector is very similar.

Figure A1. Distribution of BCs and ROCs firms by sector



Other possible approaches, such as exact matching (EM),[21] fail to preserve the balance of structural characteristics. Figure A2 presents the sectoral distribution characteristics of the EM sample versus the sample of BCs. As it can be seen, EM fails to replicate the sample of BCs, as it overweighs popular sectors such as retail trade or food and beverage, which are highly prevalent among Italian firms, but less common in the BCs sample.

Figure A2. Distribution of BCs and EM firms by sector



[21] Exact matching is a form of stratum matching that creates strata of firms based on unique combinations of covariates. Each firm is assigned to its corresponding stratum and firms that are in strata lacking either treated or control units are dropped.