

Missing Trader VAT Fraud: Evidence from Cross-Border Audits in the EU¹

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Missing trader fraud is one of the most important sources of tax revenue loss in the EU, comparable in magnitude to losses from multinational profit shifting, yet existing evidence remains limited and largely based on indirect and aggregate measures. We leverage administrative audit data covering firm-to-firm cross-border transactions across all EU Member States to study this fraud. We start by documenting new facts about the microstructure of detected schemes, showing its geographical incidence, strong concentration in wholesale and retail sectors, and reliance on repeated multi-firm, multi-country transaction networks. We then study how effective two key policy instruments – tax audits and the reverse charge reforms – are in curbing this fraud. Event-study estimates show that tax audits are very consequential: upon detection, missing traders’ survival probability falls by about 39 percentage points, corresponding to roughly three quarters of their average survival probability, and surviving firms stop the rapid growth observed before detection, with similar but smaller dynamics observed for exporting trade partners not subject to audits. In contrast, reverse charge reforms induce sizable displacement of fraud to similar sectors but in other Member States, offsetting most of the aggregate deterrence effect of the reforms. Given the contrasting evidence on the effectiveness of the two instruments, we conclude by discussing the tradeoffs involved when designing anti-fraud policy.

Keywords: VAT, Missing Trader Fraud, EU, Tax Audits, Reverse Charge Mechanism.

JEL codes: H26, K42, F14.

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1 Introduction

The value added tax (VAT) is usually viewed as self-enforcing because firms need invoices from suppliers to claim input credits. Missing trader fraud (MTF) in the EU exploits precisely this credit mechanism. In its canonical form, short-lived firms import goods or services VAT-free from another Member State, resell them domestically with VAT and disappear before remitting the tax, while the client (called the ‘broker’) claims input credits before the tax authority has discovered that the importer has gone missing (thus the name ‘missing trader’). In practice, the scheme is often organized through sophisticated cross-border networks of missing trader, broker and also buffer firms, allowing the same goods or invoices to circulate repeatedly like a carousel, while tax authorities face fragmented jurisdictional information limiting their ability to enforce effectively.

Revenue losses from MTF are substantial. Estimates suggest that the annual VAT compliance gap in the EU fluctuated between EUR 83 and 128 billion from 2019 to 2023 (European Commission 2025b; Pappadà and Rogoff 2025), with around EUR 50 billion attributed to MTF in 2023 according to one estimate (Europol 2023). These losses are comparable in magnitude to the widely discussed revenue losses from multinational profit shifting in the EU (Tørsløv, Wier, and Zucman 2023),² yet MTF has received far less academic attention. Beyond revenue losses, it is often linked to organised crime, suggesting societal costs that extend beyond routine tax non-compliance.

Despite its importance, credible evidence on the magnitude, structure, and policy responsiveness of MTF remains scarce. Existing estimates rely only on indirect approaches, such as mirror-trade discrepancies or revenue responses to reverse charge reforms, and typically remain at the aggregate country level.³ The lack of more direct micro evidence limits

²Tørsløv, Wier, and Zucman 2023’s most recent estimate is from 2015 and it amounts to about EUR 50 billion in revenue losses for the EU as a whole; Garcia-Bernardo and Janský 2024 provides a similar estimate and reviews other available estimates.

³These approaches lead to findings that vary widely in magnitude, ranging from as low as about zero to as much as about ten percent of total VAT revenue loss due to MTF in the EU (see, Table 1 of Buettner and Tassi 2023). We discuss this literature in more detail below, by also using our evidence to make statements on which of the existing estimates over- and which ones under- estimate the fraud.

our understanding of how the fraud functions, such as how the firm trade networks are set up, with which structure of firms and across which borders of the EU.⁴ This then also makes it difficult to assess whether the two main policy measures designed to fight this fraud work or not. Tax audits try to target suspicious firms and transactions as usual, but face the challenge of finding the real fraudsters within the sophisticated cross-border networks. Given these difficulties, many Member States have applied reverse charge mechanism (RCM) to the most fraud-prone products, which shifts VAT liability to the buyer, similar to a retail sales tax, mechanically removing the scope for MTF in treated transactions. Despite its popularity, its aggregate effectiveness is unclear because fraudsters may shift activity to products not covered by RCM or to Member States that have not implemented it, a potential substitution margin that the existing evidence has so far been unable to study.

This paper uses administrative audit data on firm-to-firm cross-border transactions across all EU Member States. The data comprise approximately 285,000 audited transactions conducted between 2012 and 2019, with a total value of EUR 46 billion. About 35,000 transactions, worth EUR 7.9 billion, are linked to detected fraudulent activity. These transactions are conducted by about 2,900 fraudsters including 2,500 missing trader and 190 broker firms, which we also match to data on firm-level unconsolidated financial statements and industry information from Orbis. We interpret these measures as detected fraud rather than the universe of MTF, but the data allows us to study the microstructure of detected schemes, and to estimate the relative efficacy of the two main counter-measures designed to fight the fraud, that is tax audits and RCM reforms.

The data is based on EuroFisc records, an EU-level system designed to facilitate information exchange on MTF audits among Member State tax authorities. The data originates from a leak and covers audit information from all EU Member States. While individual

⁴There is a small literature from developing countries on a somewhat similar type of fraud but which happens within countries. In this case, fake firms – often called invoice mills or ghost or shell or bogus firms – issue fraudulent VAT invoices such that their clients can claim illegitimate deductions. Carrillo et al. 2023; Waseem 2023 rely on detected cases of fraud to show that this fraud is a quantitatively large phenomenon in Ecuador and Pakistan.

tax authorities may grant access to their own administrative records, obtaining and linking the data across the entire EU is virtually impossible. This fragmentation of jurisdictional information, a main reason behind the successful use of MTF schemes by the fraudsters in the first place, likely explains the limited research on MTF to date and makes the leaked data unusually valuable.

We report three sets of results. First, we use the unique cross-border audit data to document new facts about detected MTF in the EU. First, Member States audit transactions corresponding to about five percent of the estimated VAT gap, yet only five to six percent of audits detect fraud, and detected fraud accounts for less than one percent of the estimated gap. Second, detected fraud is geographically quite concentrated geographically: the Baltics, Eastern Europe, and Southern Europe account for the largest shares relative to their size, despite not conducting more audits; with the missing trader firms primarily being set up in these countries while the broker counter-parts being set up in richer countries of West Europe. Third, concentration of fraud is also very pronounced across sectors: about three-quarters of identified fraudsters operate in wholesale and retail trade, and within that sector about two-thirds of fraudsters operate in the sub-sectors of trade in chemicals, wholesale of information and communications technology equipment, and household goods. Fourth, at the firm level, most missing traders are micro-sized firms that transact unusually large volumes relative to their size, while brokers are larger firms and often also conduct legitimate business. Fifth, at the network level, fraud schemes involve networks comprising an average of 12 firms, 57 percent of which are classified as fraudsters. These networks span 2 to 3 countries on average and involve approximately 3 repeated transactions per firm pair. Overall, these patterns suggest that MTF is not diffuse non-compliance by ordinary firms, but well-organized structures built around high-volume, short-lived mobile firms and repeated cross-border relationships.

Second, and turning to the effects of counter-measures, we study firm dynamics around fraud detection in an event-study setup. We show that the survival probability of directly

detected fraudulent and missing-trader firms falls by about 39 percentage points in the first two years after detection, corresponding to roughly three quarters of the average survival probability among treated firms. This is not surprising as it is in the nature of this fraud that the firm should go missing soon after the fraud is committed. More interestingly, we show that following the detection of fraud by the importer, its exporting partner, which in theory can be a legitimate trader, also sees a decline in its survival probability of about 13 percentage points. This appears plausible, given that about half of the exporting trade partners of fraudulent importing firms are themselves classified as fraudsters. On the intensive margin, we show that the surviving firms, stop their turbo growth of the years leading to the audit on many margins, such as total assets, sales and costs of goods sold but not with their number of employees. These effects are very large in magnitude and also hold for the exporting partner albeit with smaller magnitudes.

Third, we assess the effectiveness of RCM reforms and contrast them with audits. Using event-study designs at the NACE-4 sector level, we show that the staggered introduction of RCM strongly reduces both audit activity and detected fraud in treated sectors, with volumes falling by about one half. This is consistent with the mechanical effect of RCM: once VAT liability is shifted to the buyer, the seller can no longer collect VAT without remitting it. However, we also find substantial displacement. Following the introduction of RCM in a given country-sector, detected fraud increases in the same NACE-4 sector in countries that did not adopt RCM, but not in non-treated NACE-4 sectors within the same NACE-2 sector of the implementing country. Strikingly, audit activity does not increase in these jurisdictions, which is surprising from a policy perspective but consistent with the recurring argument that the information and policy coordination capacities of the EU Member States are too fragmented. The increase in detected fraud therefore appears to reflect genuine displacement rather than merely more intensive enforcement. Comparing the magnitudes of the direct and spillover effects, we find that displacement offsets a substantial share of the mechanical reduction in detected fraud; in our cross-country spillover accounting exercise,

the offset amounts to about 70 percent of the direct reduction.

Our paper contributes most directly to the literature on MTF in the EU. Existing work estimates the magnitude of this fraud using two, both indirect, approaches. The first approach follows the logic of Bibler, Teltser, and Tremblay 2021 and Waseem 2023 to infer baseline levels of non-compliance by evaluating the effects of reforms that should completely remove non-compliance. In our setting, the literature uses the introduction of RCM reforms. Buettner and Tassi 2023, Junttila, Koivisto, and Nivala 2024 and Cipullo et al. 2024 implement this exercise at the level of firms and find that the introduction of RCM increases reported VAT by about 5 percent in, respectively, Germany, Finland and Italy. In contrast, Heinemann 2025 reports negative effects using firm-data from across Europe, while Stiller and Heinemann 2024 and Bussy and Tassi 2025 find modest or no increases in VAT revenue at the level of countries and Bohne et al. 2023 find no reduction in country-level VAT gaps following RCM introductions. We argue that this approach is ill-suited to study MTF, since it ignores the displacement effects of fraud in response to RCM reforms, which we show are substantial. The implication of this substitution channel is that sector and firm level studies will tend to overestimate the level of fraud, while country level estimates will underestimate it. The only alternative approach has so far been the mirror-trade approach. This was first developed by Fisman and Wei 2004, and the idea is to compare trade reported by the exporter to trade happening in the same period and border but now reported from the side of the importer. Following this approach, Braml and Felbermayr 2022 estimate revenue losses from MTF to be in the order of 3 to 6 percent of VAT revenue. However, we argue that mirror-trade measures too are ill-suited to study MTF. That is because, we show that, in our sample, detected fraud is uncorrelated with trade gaps (Appendix Figure A1).

Second, and more broadly, we contribute to several strands of literature on VAT compliance, on dynamic impacts of audits, and on organised crime and firm outcomes. Our paper shows how the VAT system can be mis-appropriated despite its self-enforcing mechanism (Pomeranz 2015; Naritomi 2019), somewhat similar to the cases of invoice mills of Carrillo

et al. 2023; Waseem 2023 and mis-claimed refunds of Leite 2024, but in the cross-country setting in the EU. It also relates to a growing body of work which studies the dynamic responses of firms (and individuals) to tax audits (Kleven et al. 2011; DeBacker et al. 2018; Best, Shah, and Waseem 2021; Advani, Elming, and Shaw 2023; Kotsogiannis et al. 2024; Li and Wang 2026; Harju et al. 2025) including the network effects of audits on non-targeted firms (Boning et al. 2020; Almunia et al. 2023; Lediga, Riedel, and Strohmaier 2026) by being the first example of studying cross-border audits across multiple countries.⁵ Finally, our results relate to the literature on organised crime and firm outcomes (Bianchi et al. 2022; Fenizia and Saggio 2024; Slutzky and Zeume 2024; Arellano-Bover et al. 2024) by extending the study to tax fraud rather than just tax evasion or avoidance.

2 Institutional Background

2.1 The VAT system in the EU

VAT is an indirect consumption tax imposed at each stage of the value chain. The EU VAT system is largely harmonized through the VAT Directive⁶, although Member States retain the flexibility to set their own rates, subject to a minimum standard rate of 15 percent.⁷ VAT applies to all sales by businesses that are eligible for VAT⁸, making it a tax collected at every stage of production.

When a seller conducts a transaction, VAT is included in the gross price charged to the buyer, who pays this amount in full. The seller then reports the VAT portion to the tax authority, effectively acting as a tax collector on behalf of the government. At the same time, businesses incur VAT on inputs, such as goods or services purchased for production,

⁵Two further technical papers develop algorithms to help tax authorities detect potential missing trader like fraudsters using administrative data in India (Mittal, Reich, and Mahajan 2018) and Bulgaria (Alexopoulos et al. 2025).

⁶Council Directive 2006/112/EC of 28 November 2006 on the common system of value added tax.

⁷Reduced rates may apply to essential goods.

⁸Many EU Member States provide exemptions or simplified schemes for small businesses below a certain turnover threshold, relieving them from VAT registration or reporting obligations.

which can be deducted from the VAT collected on sales. This mechanism ensures that VAT is effectively levied only on the value added at each stage. The VAT liability is calculated as the difference between the VAT collected from customers and the VAT paid on inputs, which the seller remits to the tax authority.

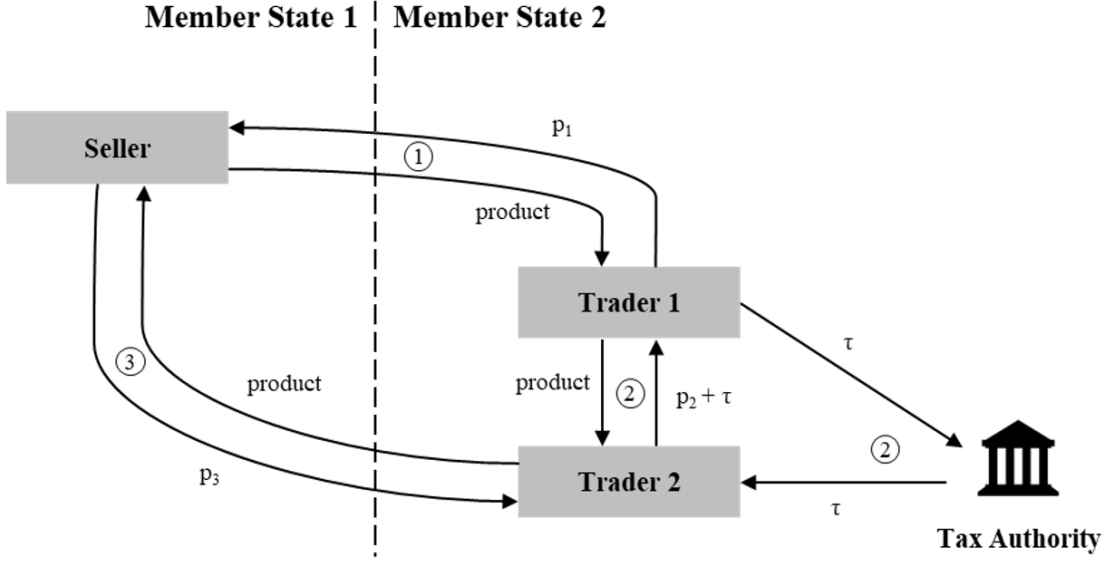
Collecting VAT along the value chain offers a notable advantage. Since buyers are only entitled to deduct input VAT from their VAT liability if they have a corresponding invoice, they are incentivised to ensure accurate transaction reporting. Thus, the responsibility for assessing the tax base is delegated to the buying firms, alleviating the burden on the tax authority (Bussy and Tassi 2025). Special rules apply to intra-community sales between EU Member States due to the removal of border and customs controls within the EU.⁹ These rules, however, also represent a major vulnerability of the system with respect to VAT fraud. Intra-community transactions are generally classified as either Business-to-Business (B2B) or Business-to-Consumer (B2C). Intra-community B2C transactions follow the destination principle, according to which goods and services are taxed in the country where they are consumed. In contrast, intra-community B2B transactions are zero-rated: exports leave the originating Member State tax-free, while the VAT paid on inputs remains deductible for the exporter (Keen and Smith 1996). The importing firm must declare an intra-community acquisition in its country. At the same time, the corresponding input VAT is deductible, resulting in a net VAT liability of zero at the moment of importation. VAT is only remitted once the importing firm sells the goods domestically and collects output VAT from the final buyer. Figure 1 illustrates the VAT treatment of cross-border trade between compliant firms.

2.2 Missing Trader Fraud in the EU

Despite the incentives for buyers to ensure accurate VAT reporting, the EU VAT system and its credit mechanism create specific opportunities for fraud (Keen and Smith 2006). In 2023, the EU VAT gap was estimated at around EUR 128 billion, corresponding to

⁹For the economic implications of abolishing border controls, see Cnossen 1983.

Figure 1: Cross-Border Trade with Compliant Firms



Notes: This figure illustrates the functioning of the EU VAT system in cross-border trade between VAT compliant firms.

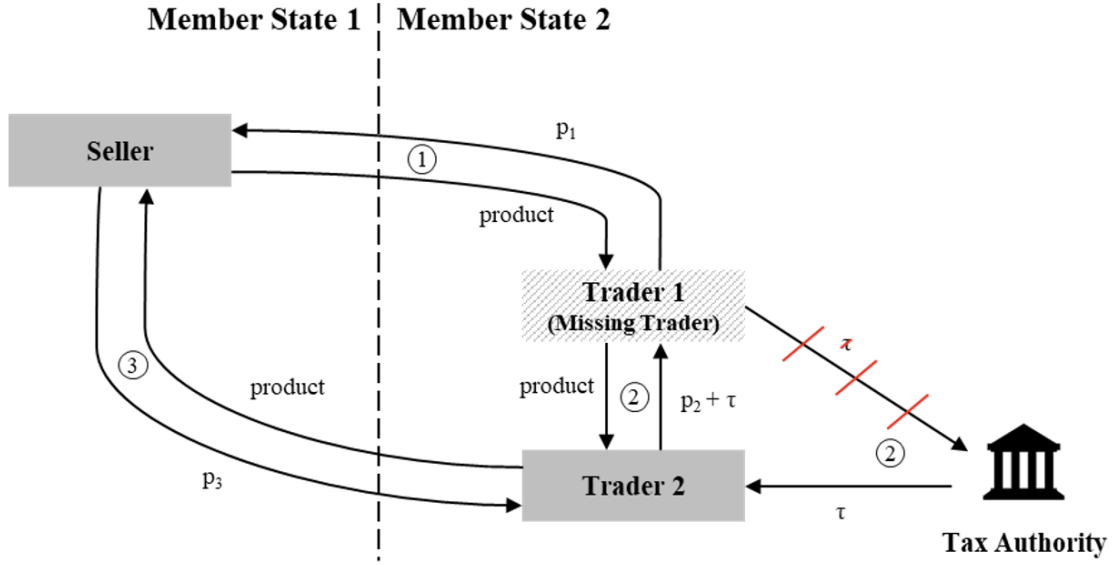
approximately 9.5 percent of total tax revenues (European Commission 2025a). Cross-border VAT fraud, commonly referred to as MTF or carousel fraud, constitutes the most significant component of this gap, according to one estimate costing the governments of EU Member States about EUR 50 billion a year (Europol 2023).

MTF is a sophisticated tax evasion scheme that exploits a central feature of the EU VAT system, namely the destination principle. Goods targeted in MTF are typically high in value and turnover but low in volume, including mobile phones, computer components, metals, meat, wholesale oil and grain, and cosmetic products (Borselli 2011; Van Brederode and Pfeiffer 2015). Due to its scale, professional organization, and links to organized crime, MTF attracts substantial institutional attention within the EU.

A simplified depiction of MTF is shown in Figure 2.¹⁰ Trader 1 in Member State 2 imports tax-free goods and services from the seller in Member State 1 given that intra-community B2B transactions are zero-rated. Trader 1 then resells the goods to Trader 2, charges output VAT on this sale, but fails to remit the collected VAT to the tax authority.

¹⁰Depiction based on European Commission 2018.

Figure 2: Cross-Border Trade with Missing Trader or Carousel Fraud

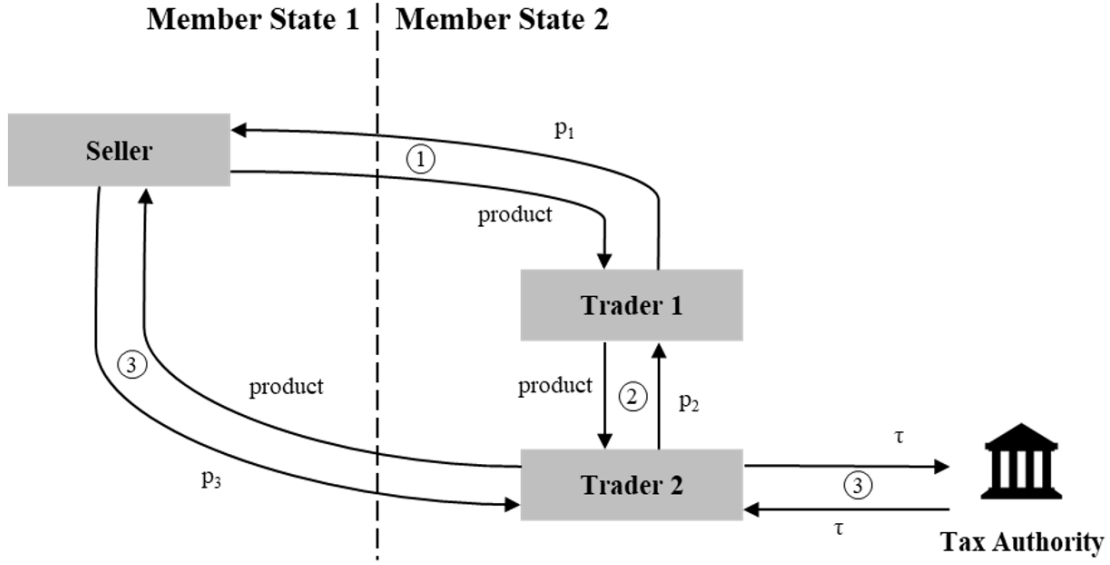


Notes: This figure illustrates the basic functioning of missing trader or carousel fraud.

Trader 2, which may be a broker, uses the invoice from Trader 1 to claim the corresponding input VAT credit. The revenue loss arises in Member State 2 because the tax authority recognizes the input VAT credit while the missing trader does not remit the matching output VAT.

In the carousel version, Trader 2 does not sell to a final consumer but re-exports the goods to the initial seller, or to another conduit firm, in Member State 1, thereby closing the trading circle as shown in Figure 2 (European Commission 2018). The same goods or invoices can then circulate repeatedly, generating repeated claims for input VAT credits while the missing trader disappears before remitting output VAT. In practice, the fraud scheme is often obscured by using additional buffer companies that intermediate the transactions either domestically or across borders, but which are not necessarily involved in the fraud (Keen and Smith 2006). This circular scheme is often repeated multiple times, each time resulting in the fraudulent collection of a VAT credit from the tax authority of Member State 2 corresponding to the amount of VAT charged on the trade between Trader 1 and Trader 2.

Figure 3: Cross-Border Trade with Reverse Charge Mechanism



Note: This figure illustrates the functioning of the RCM within the EU VAT system

2.3 Reverse Charge Mechanism

Because MTF exploits cross-border information frictions, combating it requires extensive coordination between Member States (De La Feria 2019). An alternative counter-fraud policy introduced by the EU is the RCM, which shifts the liability to account for VAT from the seller to the buyer. Under this mechanism, the seller issues an invoice that excludes VAT, while the customer calculates and pays the VAT directly to the tax authority.¹¹ As illustrated in Figure 3, this mechanism effectively removes the opportunity for a missing trader to collect VAT from customers without remitting it to the tax authority. Since Trader 1 no longer receives VAT payments from Trader 2, the central channel through which MTF generates tax losses is closed.

The RCM exists in both cross-border and domestic contexts. For cross-border supplies of services, the place of supply is generally where the customer is established¹². If the supplier is not established in that Member State, the customer must account for the VAT¹³. This

¹¹Council Directive 2006/112/EC, Articles 194, 196, 199, 199a, 199b; invoicing requirements: Article 226(11a).

¹²Council Directive 2006/112/EC, Art. 44.

¹³Council Directive 2006/112/EC, Art. 196.

arrangement removes the obligation for foreign suppliers to register for VAT in each Member State and ensures that tax is collected where the service is actually used. For domestic supplies by non-established traders, Member States may also apply the RCM, making the customer liable for VAT. The specific implementation is voluntary for Member States. The RCM has been introduced selectively for fraud-prone goods and services, such as electronics, construction work, telecommunications, and certain high-value products, in line with Articles 199 and 199a of the VAT Directive. Initially, these provisions were temporary derogations, which have been extended several times. The Quick Reaction Mechanism¹⁴ allows Member States to apply the RCM on short notice in response to emerging VAT fraud.

Introduced in 2006, the RCM initially applied to construction work, staff supply, waste, and immovable property.¹⁵ In 2010, its scope was expanded to include greenhouse gas emission allowances through Article 199a.¹⁶ In 2013, further extensions allowed Member States to apply the RCM, optionally and temporarily, to mobile phones, gas and electricity, telecommunications services, game consoles, tablets, laptops, cereals, industrial crops, and metals.¹⁷ Additional Member States were authorized to apply the RCM to specific goods and services under Article 395.¹⁸ Consequently, the adoption of RCM has been staggered across Member States and product categories, reflecting both differences in national implementation and the sector-specific risk of VAT fraud (De La Feria 2019). An overview of the applicability of RCM regimes within the EU Member States as of 2018 can be found in Table A4 in the Appendix.

2.4 Missing Trader Fraud in Practice: A Case Study

This section illustrates how the MTF mechanisms described in Section 2.2 operate in practice using an example of a detected fraud case. The case concerned a large cross-border

¹⁴Council Directive 2006/112/EC, Art. 199b.

¹⁵Council Directive 2006/112/EC, Art. 199.

¹⁶Council Directive 2006/112/EC, Art 199a, as introduced by Directive 2010/23/EU.

¹⁷Council Directive 2006/112/EC, Article 199a, as amended by Directive 2013/43/EU.

¹⁸Council Directive 2006/112/EC, Article 395.

VAT carousel fraud in the IT hardware sector, investigated by German authorities and tried in Augsburg.¹⁹ Newspaper reporting links the trading chains to Devil AG, a German IT distributor, other firms, and foreign intermediaries. The investigation involved more than one hundred suspects, and authorities estimated VAT losses of approximately EUR 120 million. Before insolvency proceedings, Devil AG reported operating revenue of EUR 362.1 million and employed 112 workers.

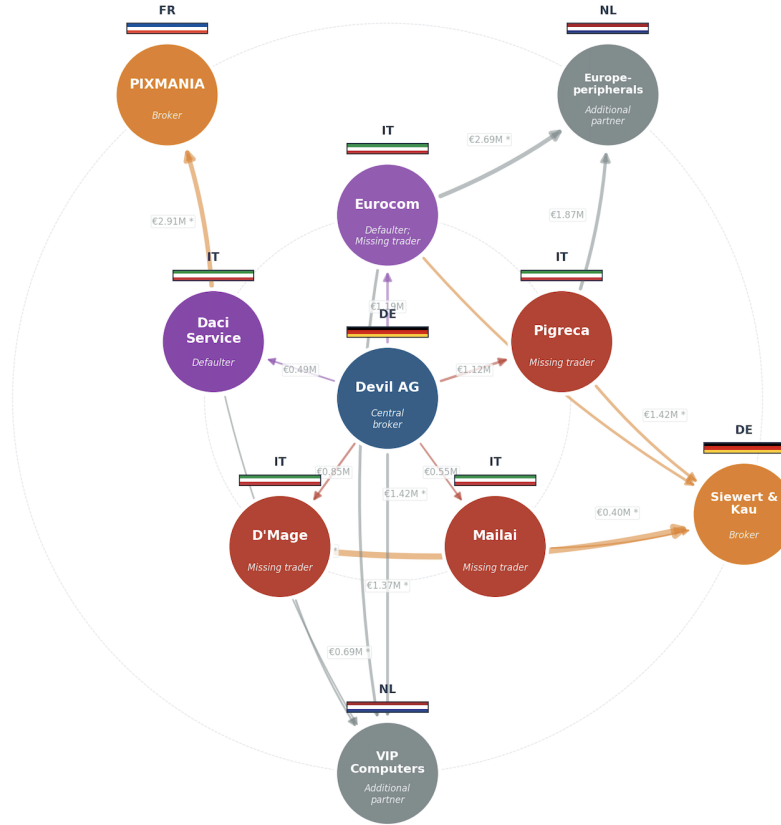
Figure 4 shows a simplified version of the fraud network surrounding Devil AG as reconstructed from the audit data. To keep the figure readable, we focus on 16 selected flows involving Devil AG, its fraud-classified counterparties, and their largest additional partners. The full transaction network is substantially larger. The total volume of transactions in the full network adds up to approximately EUR 500 million and includes 839 unique firms of which 108 firms are identified fraudsters.

Devil AG is placed at the center of the network, connected to Italian firms classified as missing traders or defaulters in our audit data, including Eurocom, Pigreca, Mailai, D'Mage, and Daci Service. In the flow shown by the arrows, goods move from Devil AG in Germany to the detected missing traders in Italy and then onward to two firms one in France and one back in Germany which are labeled as brokers in our data and also to two additional trading partners in the Netherlands which are not labeled as brokers or other fraudsters. Notably in the audit data, Devil AG itself is not classified as a missing trader, broker, buffer, or as any other fraudster type. This is consistent with newspaper reporting where certain executives of Devil AG, such as Axel Grotjahn, participated in the scheme but the firm itself was not charged with MTF-related charges. However, the firm went through insolvency proceedings, before re-opening as a re-branded firm named Abwicklungs AG.

The tax loss arises on the resale leg: the missing trader charges VAT to the next firm in the chain but fails to remit it. The goods can then be re-exported to the detected broker

¹⁹Focus, available at: https://www.focus.de/magazin/archiv/der-millionen-steuergeldbetrug-report_id_2424744.html (26.05.2026); IT-Business, available at: <https://www.it-business.de/mehrjaehrige-haftstrafen-fuer-umsatzsteuerbetrug-a-424196/> (26.05.2026).

Figure 4: A Case Study of a Missing Trader Fraud Scheme



Notes: This figure illustrates the partial MTF network surrounding Devil AG as suggested by the EuroFisc data.

firms allowing these firms to claim input VAT credits. As a concrete example, Figure 4 shows how Devil AG sells to the missing trader firm Pigreca goods with a total value of approximately EUR 1.12 million. This firm was based in Torino and, according to Orbis data, operated in the wholesale of computers, peripheral equipment, and software. In 2009, the firm reported operating revenue of just EUR 136,000 and total assets of EUR 226,000, while no workers were reported. Pigreca then sells to Siewert & Kau, a broker located in Germany, which is likely the firm claiming the input VAT credit.

The detected broker Siewert & Kau also buys from the three other missing traders based in Italy to which Devil AG sells. In addition, Pigreca also sells to Europe-peripherals, located in the Netherlands, which is not confirmed to be a broker in the audit data but potentially looks like one in this scheme. Europe-peripherals also buys from Eurocom, another Italian

missing trader, which in turn buys from Devil AG and sells to Pigreca. These links suggest that the fraud-classified counterparties were embedded in an overlapping cross-border trading network rather than appearing only as isolated transactions with Devil AG.

3 Data

3.1 EuroFisc Data Source and Construction

To quantify the extent of cross-border VAT fraud, we use administrative data from EuroFisc, as stored by the Bulgarian tax authorities. EuroFisc is an EU network established in 2010 to facilitate cooperation and exchange of information among Member States in the field of combating VAT fraud. The network enables tax authorities to exchange information, intelligence, and risk assessments related to potential fraud cases, helping them identify and target high-risk transactions or entities involved in fraudulent activities. EuroFisc includes four working fields, one of which is dedicated to MTF (i.e. Working Field 1: Missing Trader Intra-Community Fraud) (German Federal Audit Office 2015). The data became publicly available through a data leak of the Bulgarian tax authorities, but it included the data from all the Member States of the EU.²⁰

We follow the guidance of Alstadsæter, Collin, and Økland 2025 on the responsible use of leaked data. Furthermore, the project received approval from the ethics committee of the ZEW – Leibniz Centre for European Economic Research, confirming that the use of the data does not raise ethical concerns for participants, researchers, or other parties potentially affected by the study.

We use three distinct EuroFisc data sources. Two sources contain audited cross-border transactions between non-anonymized firms reported between 2012 and 2019. We combine these transaction-level datasets and harmonize VAT identification numbers, country codes,

²⁰Reuters, available at: <https://www.reuters.com/article/world/in-systemic-breach-hackers-steal-millions-of-bulgarians-financial-data-idUSKCN1UBOMA/> (14.01.2026).

transaction dates, and transaction amounts. To avoid repeated observations, we remove duplicate transaction records based on VAT identification numbers, transaction dates, country pairs, and transaction amounts. The third source contains firm-level EuroFisc classifications, which we use to identify fraudulent firms. Firms are classified into several categories, including missing traders, brokers, remote traders, cross-invoicers, defaulters, buffer traders, and cases involving hijacked VAT numbers. We merge these firm-level classifications to the audited transaction data using VAT identification numbers. Audited transactions involving a fraudulent importing firm are classified as fraudulent audits. We refer to these firms as fraudsters and, where relevant, distinguish separately between missing traders and brokers. The full data selection process can be found in Panel A of Table A1.

3.2 EuroFisc Sample and Benchmarks Against VAT Gaps

Overall, 2,942 uniquely identified fraudsters can be matched to audited cross-border transactions in the EuroFisc data. Missing traders account for the majority of detected fraudulent firms throughout the sample period. Of all fraudulent firms, 2,462 firms are classified as missing traders and 186 as brokers. Table 1 provides an overview of the merged EuroFisc transaction-level data. In total, the dataset contains 284,947 audited cross-border transactions with a combined transaction volume of EUR 45.53 billion. Among these transactions, 35,375 are linked to fraudulent activity, corresponding to a total fraud volume of EUR 7.87 billion.

Since it is not clear whether the leaked files represent the complete EuroFisc database or only an extract thereof, we aggregate the transaction-level data to the annual level and benchmark the resulting transaction and fraud volumes against official VAT gap estimates published by the European Commission. The corresponding results are reported in Table 2. The audited transaction volume covered by the data amounts to roughly 3 to 5 percent of the estimated VAT gap, while detected fraud volume is considerably smaller. These magnitudes are consistent with the interpretation that the data capture reported suspicious activity

Table 1: Yearly Overview of EuroFisc Data

Year	Audits		Fraudulent Transactions		Fraudulent Firms		
	<i>Volume</i> (bil. EUR)	<i>Number</i> (#)	<i>Volume</i> (mio. EUR)	<i>Number</i> (#)	<i>Fraudsters</i> (#)	<i>Missing Traders</i> (#)	<i>Brokers</i> (#)
2012	6.25	48,058	1,895.85	10,754	1,055	597	179
2013	7.95	40,706	1,666.92	4,854	469	208	114
2014	8.67	55,721	883.21	3,995	259	88	94
2015	8.35	55,185	870.65	4,428	287	158	77
2016	7.77	39,194	1,285.69	5,306	729	624	63
2017	4.64	27,955	993.54	4,492	1,120	1,016	63
2018	1.49	14,064	254.29	1,410	660	600	35
2019*	0.40	4,064	19.18	136	76	39	23
All	45.53	284,947	7,869.32	35,375	2,942	2,462	186

Notes: This table presents annual summary statistics of the EuroFisc data. Audit volume is reported in billion EUR, while fraud volume is reported in million EUR. The term fraudster includes various fraud types: missing traders, brokers, remote traders, cross-invoicers, defaulter, buffer trader and hijacked VAT numbers of firms. Missing traders and brokers are subgroups of fraudsters specifically associated with MTF. Data marked with * indicate partial coverage

rather than the universe of missing VAT revenues measured in the VAT gap estimates. Accordingly, throughout the analysis we interpret our fraud measures as detected VAT fraud, not as total VAT fraud. The figures for 2019 are substantially lower, which is plausible given that the data leak occurred in June 2019 and therefore covers only part of the year.

3.3 EuroFisc to Orbis Merge

We link transaction-level EuroFisc records to firm-level financial and industry data from Bureau van Dijk’s Orbis database. Orbis provides unconsolidated financial statements and industry classifications for European firms. We clean the Orbis financial data by retaining unconsolidated 12-month accounts, keeping one observation per firm-year, requiring at least one core activity variable to be observed, and applying plausibility restrictions to fixed assets, sales, and employment. Continuous financial variables are winsorized at the 1st and 99th percentiles of the cleaned Orbis firm-year distribution.

Table 2: Benchmark against VAT Gap Figures

Year	VAT Gap (bil. EUR)	Audit Volume (bil. EUR)	Audit (%)	Fraud Volume (mio. EUR)	Fraud (%)
2012	168.54	6.25	3.71	1,895.85	1.12
2013	163.99	7.95	4.85	1,666.92	1.02
2014	162.12	8.67	5.35	883.21	0.54
2015	152.19	8.35	5.49	870.65	0.57
2016	144.34	7.77	5.38	1,285.69	0.89
2017	146.10	4.64	3.18	993.54	0.68
2018	141.60	1.49	1.05	254.29	0.18
2019*	138.62	0.40	0.29	19.18	0.01

Notes: This table compares the VAT gap estimations of the European Commission with the calculated fraud volume from the EuroFisc data. Data marked with * indicate partial coverage.

Sources of VAT gap estimates: European Commission 2020, European Commission 2021, European Commission 2022.

We match firms across the two data sources using VAT identification numbers.²¹ The VAT-ID based merge performs similarly across treatment groups. Among importing VAT identifiers, we match 70.9 percent of audited firms, 69.1 percent of detected fraudsters, 70.1 percent of missing traders, and 76.3 percent of brokers to at least one Orbis BvD identifier. When considering VAT identifiers observed on either side of a transaction, the corresponding match rates are 70.7, 68.4, 69.6, and 68.8 percent. The analysis is restricted to the period 2012–2019. The matched EuroFisc–Orbis dataset contains 32,355 uniquely identified importing firms subject to EuroFisc audits. Of these audited importers, 787 are classified as detected fraudsters, including 603 missing traders and 106 brokers. To construct appropriate comparison groups, we retain non-audited firms from Orbis operating in the same country-industry cells as firms observed in the EuroFisc audit and fraud datasets. Some treated EuroFisc firms can be matched to Orbis financial data but do not have observed NACE-4 industry information. Rather than dropping these treated firms, we assign them to NACE-4 industry 4651, wholesale of computers, computer peripheral equipment and

²¹Firms are identified in Orbis by their BvD ID. In some cases, more than one BvD ID is linked to the same VAT identification number. Because the EuroFisc data identify audited firms by VAT identification number, we classify all BvD IDs sharing a treated VAT ID as treated. This avoids assigning potentially treated firms to the comparison group, although it may introduce a bias towards zero in our results.

software, which is the modal observed NACE-4 industry among matched treated firms and a central sector in the detected MTF activity. We then construct country-NACE-4 comparison samples around the treated firms. Detailed information on the sample selection is reported in Panel B of Table A1.

Linking transaction-level EuroFisc records to Orbis involves several limitations. VAT identification numbers are not always available for detected fraudsters and, when available, cannot always be matched reliably to Orbis records. This issue is particularly important for firms that existed only briefly, operated as shell entities, or left little observable economic footprint, which are precisely the types of firms frequently associated with MTF. Moreover, tax authorities report anecdotal evidence that fraudsters sometimes use stolen or misappropriated VAT identification numbers of other firms. In such cases, the legal entity observed in Orbis may differ from the economic entity responsible for the fraudulent transaction, a pattern that is also partially visible in the EuroFisc data. Consequently, the matched Orbis sample likely captures the more established and traceable segment of fraudulent firms.

4 Anatomy of Missing Trader Fraud

4.1 Regional Distribution of Audits and Detected Fraud

We start by documenting the distribution of audited transactions and detected fraud across Europe. Table 3 reports region-level aggregates. The table presents audit volume and detected fraud volume for all fraud types combined, as well as separately for missing traders and brokers. Eastern Europe and Western Europe account for the largest shares of audit volume, with 34.3 and 36.3 percent, respectively. However, the regional distribution differs substantially across fraud types. Total detected fraud volume is most heavily concentrated in Western Europe, which accounts for 49.7 percent of the fraud, followed by Eastern Europe and Southern Europe with shares of 25.0 and 21.2 percent, respectively. Missing trader volume is concentrated primarily in Eastern and Southern Europe, which together

Table 3: Region-Level Audits and Fraud

Region	Audits		All Fraud		Missing Traders		Brokers	
	<i>Volume</i> (bil. EUR)	<i>Share</i> (%)	<i>Volume</i> (mio. EUR)	<i>Share</i> (%)	<i>Volume</i> (mio. EUR)	<i>Share</i> (%)	<i>Volume</i> (mio. EUR)	<i>Share</i> (%)
Baltics	2.64	5.79	166.27	2.11	92.29	2.61	54.23	2.17
Eastern Europe	15.61	34.28	1,969.11	25.02	1,584.42	44.79	92.00	3.67
Scandinavia	0.90	1.97	154.12	1.96	19.68	0.56	132.36	5.29
Southern Europe	9.85	21.63	1,669.46	21.21	1,387.11	39.21	64.27	2.57
Western Europe	16.54	36.33	3,910.35	49.69	453.82	12.83	2,160.85	86.31
All	45.53	100.00	7,869.32	100.00	3,537.32	100.00	2,503.72	100.00

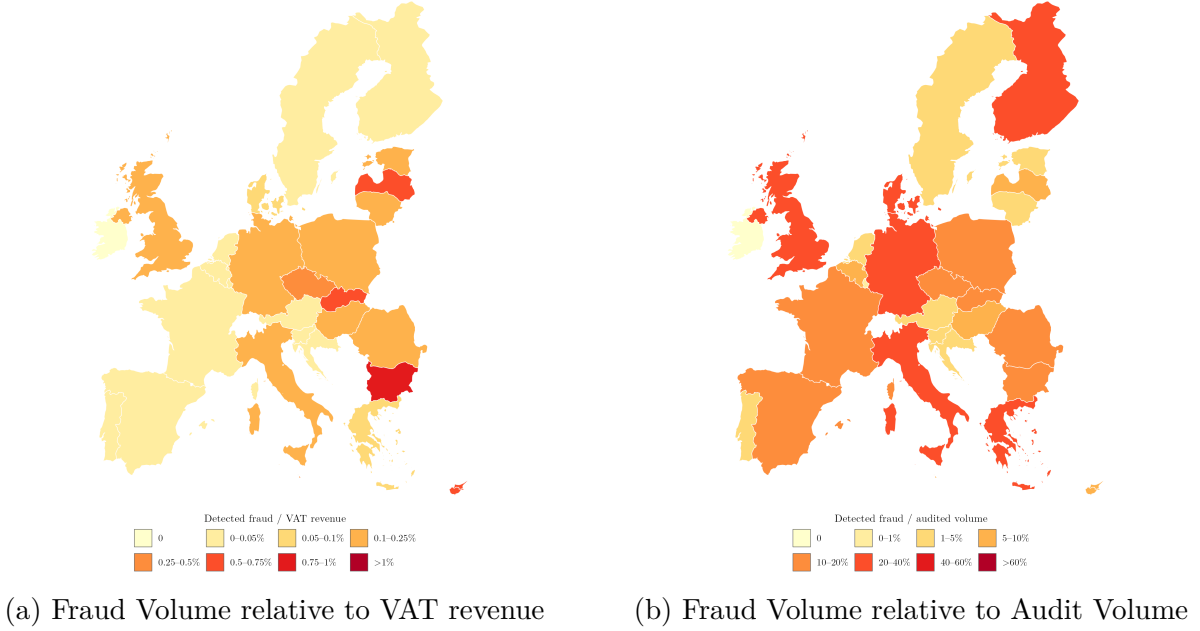
Notes: This table reports the regional distribution of audits and detected fraud in the EU. Countries are grouped into regions as follows: Baltics (Estonia, Latvia, Lithuania), Eastern Europe (Bulgaria, Czech Republic, Hungary, Poland, Romania, Slovakia, Slovenia), Scandinavia (Denmark, Finland, Sweden), Western Europe (Austria, Belgium, Germany, France, Ireland, Luxembourg, the Netherlands, United Kingdom), and Southern Europe (Cyprus, Spain, Greece, Croatia, Italy, Malta, Portugal). Audit volume is reported in billion EUR, while fraud volumes are reported in million EUR.

account for 84.0 percent of total missing trader fraud. Broker-related fraud, by contrast, is overwhelmingly concentrated in Western Europe, which accounts for 86.3 percent of total broker volume.

Figure 5 shows fraud volumes relative to each country’s VAT revenue and audit volume. While Scandinavia and Western Europe exhibit relatively low fraud-to-VAT revenue ratios, the Baltics and Southern Europe display the highest levels of detected fraud. However, scaling fraud volume by audit activity reveals a different pattern: Western Europe exhibits the highest fraud-to-audit ratio.

Moving to country borders, Table 4 lists the most common country pairs by audit and detected fraud volumes. The largest audited transaction volumes on absolute numbers are concentrated in pairs involving Germany, Italy, and the Netherlands. The ranking by detected fraud volume partly overlaps with the audit ranking: Netherlands–Germany and Poland–Germany appear among the top pairs in both columns. At the same time, several high-fraud pairs involve the Italy and the United Kingdom as the importing countries.

Figure 5: Scaled Country-level Fraud Volume



Notes: This figure shows fraud volume relative to VAT revenue by importing country in Panel (a) and fraud relative to audit volume in Panel (b). Audit volume refers to the total value of audited cross-border transactions in the EuroFisc data. Detected fraud volume refers to audited transactions involving a fraudulent firms as an importer. Values are expressed as percentages of country-level VAT revenue over the years 2012 to 2019.

4.2 Sectoral and Firm-Level Incidence

Next, we use the merged EuroFisc-Orbis sample to document the concentration of audits and detected fraud across sectors and firm types.

Figure 6 presents the industry distribution of audited firms and detected fraudsters. Panel A shows that EuroFisc audits are highly concentrated in wholesale and retail trade (NACE sector G), with manufacturing, information and communication, and professional services accounting for much smaller shares. Panel B shows that this concentration is even stronger among detected fraudsters: most fraud-classified firms operate in wholesale and retail trade, consistent with the fact that MTF typically relies on cross-border trade in goods. Panels C and D provide a more detailed breakdown within wholesale and retail trade. Among both audited firms and detected fraudsters, the largest sub-industries are wholesale of chemicals and wholesale of ICT equipment. These sectors are natural targets

Table 4: Top 15 Country-Pairs by Audit and Fraud Type

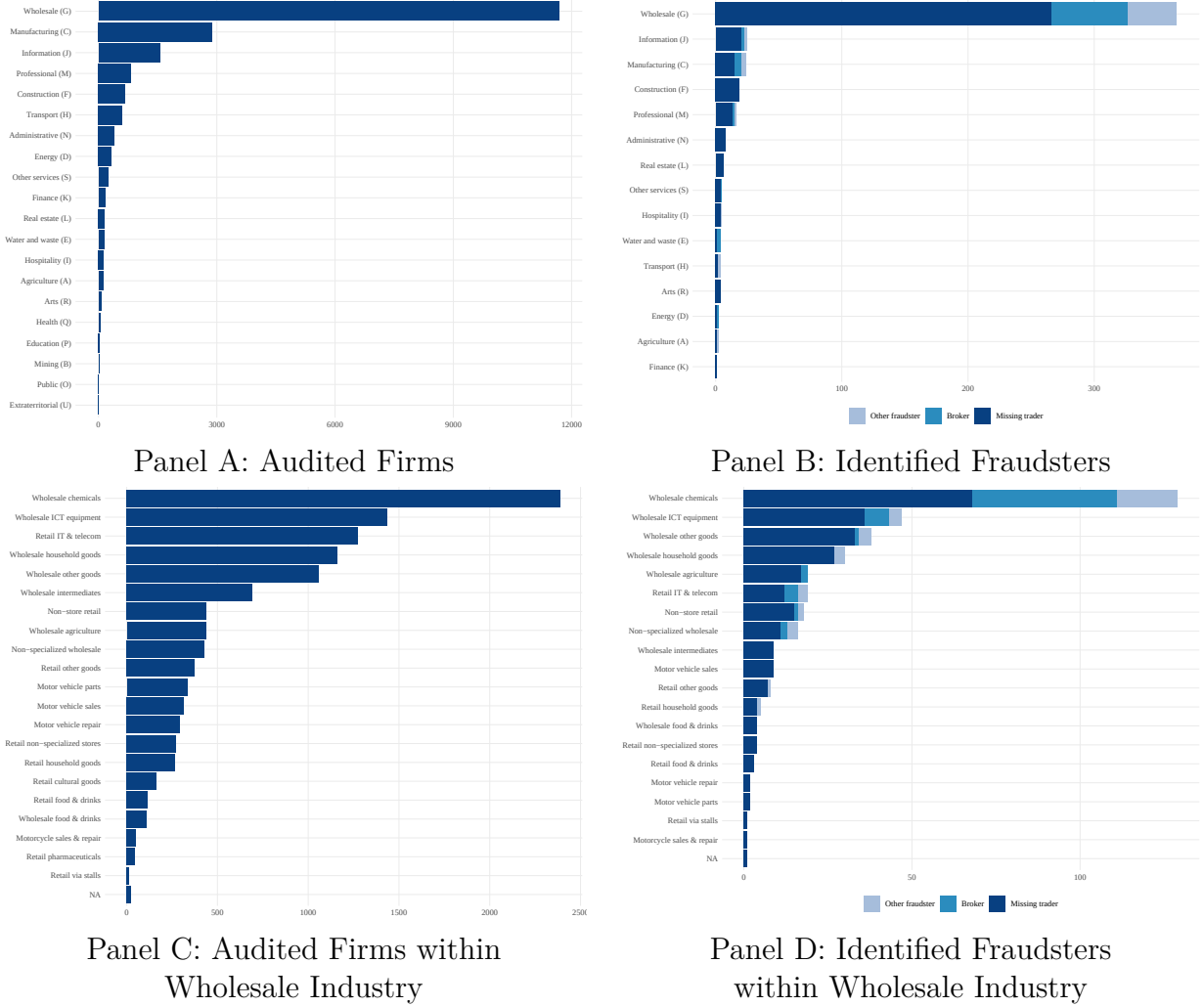
Audits			Total Fraud			Missing Trader		
Exporter	Importer	Volume (mio. EUR)	Exporter	Importer	Volume (mio. EUR)	Exporter	Importer	Volume (mio. EUR)
NL	DE	1,779.53	NL	DE	565.37	NL	IT	175.06
SK	IT	1,030.51	SK	GB	498.18	HU	IT	142.02
PL	DE	870.40	PL	DE	327.51	AT	CZ	106.84
NL	GB	863.44	FR	GB	291.35	CY	IT	94.50
NL	IT	775.89	NL	IT	247.20	PT	IT	74.38
CY	PL	725.08	FR	DE	227.47	GR	BG	48.82
FR	DE	698.81	AT	DE	150.06	NL	DE	37.58
BE	DE	632.23	HU	IT	145.35	BE	GB	18.47
LV	PL	597.22	GR	BG	127.39	FR	DE	15.19
FR	GB	549.84	NL	GB	125.99	PL	DE	6.36
NL	FR	532.64	IE	GB	116.86	IE	GB	4.26
NL	BG	531.30	PT	IT	110.02	NL	GB	3.59
DE	PL	531.02	BE	GB	108.94	AT	DE	3.24
SK	GB	514.76	AT	CZ	106.87	SK	IT	1.91
AT	CZ	510.47	CY	IT	102.07	FR	GB	0.39

Notes: This table reports the top 15 country-pairs in the EuroFisc data separately ranked by audit volume, total fraud volume, and missing trader volume. All values are reported in million EUR.

for MTF because they involve goods that are high in value, frequently traded, and relatively easy to move across borders.

Figure 7 reports the corresponding firm-size distribution. Both audited firms and detected fraudsters are concentrated among micro firms with fewer than ten employees. This pattern is particularly pronounced for missing traders, which is consistent with the role of short-lived, low-capacity firms in MTF schemes. Such firms can transact large values relative to their observed size and then disappear before remitting VAT. Brokers, by contrast, are more likely to appear among larger firms, consistent with their role as more established intermediaries that may combine legitimate business activity with participation in fraudulent trading chains. Overall, Figures 6 and 7 show that detected MTF is not spread evenly across the firm population, but is concentrated in specific goods-trading sectors and among firm types whose observed characteristics match their roles in the fraud scheme.

Figure 6: Industry Sectors of Audited and Fraudulent Firms



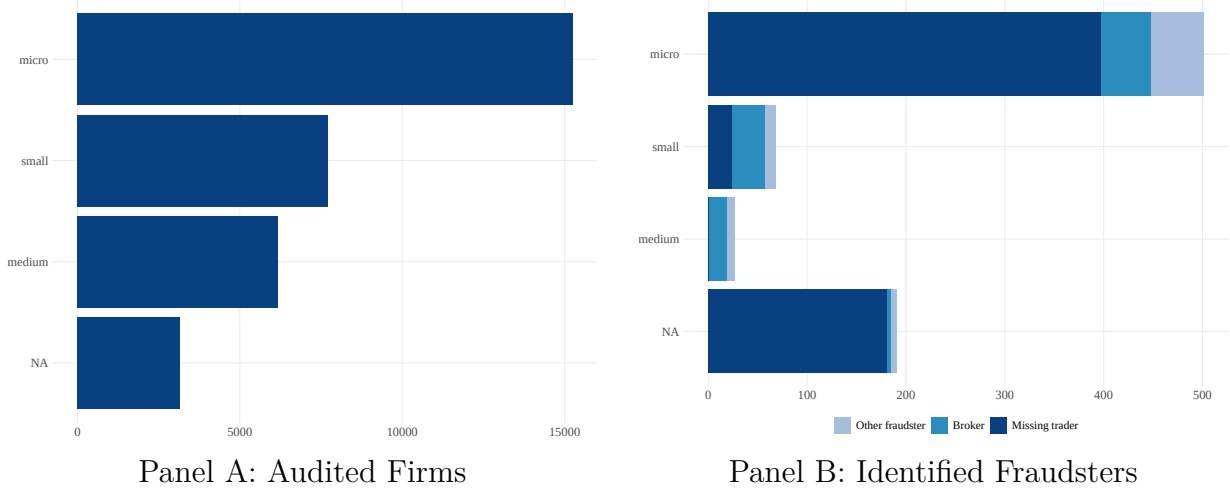
Notes: This figure shows the industry distribution for audited firms in Panel A and fraudsters in Panel B. Panel C and D show the subindustry within the wholesale industry. The figure includes all firms with available industry information in Orbis. The x-axis depicts the number of firms.

5 Tax Audits: Firm Dynamics Around Fraud Detection

5.1 Empirical Strategy

We construct three firm-level samples to evaluate how EuroFisc audits and the detection of MTF are associated with firm survival and performance. The audit sample is used to estimate the effects of EuroFisc audits. Its treatment group consists of audited firms, while

Figure 7: Firm Size of Audited and Fraudulent Firms



Notes: This figure shows the firm size distribution for audited firms in Panel A and for fraudsters in Panel B. Both panels use the same size classification based on the number of employees: micro (<10), small (10–49), medium (50–249). The x-axis shows the number of firms.

its control group consists of non-audited firms operating in the same country-industries as audited firms. The fraud sample is used to study outcomes associated with detected fraud. Its treatment group consists of audited firms identified as fraudulent firms, while its control group consists of non-audited firms operating in country-industries in which at least one fraudster is detected. We additionally construct a firm-year survival panel based on the fraud sample. For each firm, the panel starts in the first year in which the firm is observed in Orbis. Firms are therefore not coded as absent before their first appearance in the data, while disappearances after first observation are coded as non-survival. This sample is used to analyse firm survival after fraud detection.

Table A2 reports summary statistics for both firm-level samples. Panel A reports the firm survival sample used to analyse the extensive margin effects of detected fraud. On average, treated fraud firms exhibit lower survival probabilities than control firms, with average survival rates of 53 percent and 68 percent, respectively. Panel B presents the detected fraud sample. Detected fraudsters are, on average, also larger than firms in the corresponding control group. Average total assets amount to EUR 5.11 million, compared with EUR 1.52 million for control firms. Detected fraudsters employ, on average, 17 workers

compared with 10 among control firms. Panel C presents the audit sample. Audited firms are substantially larger than control firms across all reported dimensions. Average total assets amount to EUR 10.95 million for audited firms, compared with EUR 1.69 million for control firms. Audited firms also employ more workers, with an average of 45 employees compared with 10 among control firms.

Audits and fraud detection occur at different points in time across firms, which allows us to exploit variation in treatment timing to estimate dynamic changes around these events in a staggered difference-in-differences (DiD) framework. We estimate event-study specifications separately for the extensive and intensive margins. For the extensive margin, we study firm survival using the fraud survival panel described above and estimate a linear probability model (LPM). The LPM is well suited for this setting because the outcome is binary and the coefficients can be interpreted directly as percentage-point changes in survival probabilities Angrist 2001.

To measure the association between fraud detection and firm survival on the extensive margin, we estimate the following LPM regression for firm i and year t :

$$Survival_{it} = \alpha_i + \sum_{k \neq -1} \beta_k \cdot \text{Fraud}_{it}^{(k)} + \lambda_t + \varepsilon_{it}. \quad (1)$$

Here, $Survival_{it}$ is an indicator equal to one if firm i is observed in Orbis in year t and zero otherwise. The outcome is constructed on a firm-year panel based on the fraud sample that starts in the first year in which each firm is observed in Orbis. Firms are therefore not coded as absent before their first appearance in the data, while disappearances after first observation are coded as non-survival. This allows us to measure survival within the observed firm population while avoiding artificial non-survival spells before firm entry. The treatment indicators $\text{Fraud}_{it}^{(k)}$ capture event time relative to the first year in which firm i is identified as a fraudster in EuroFisc. The event-time index k denotes the number of years before or after fraud detection, with the year prior to detection ($k = -1$) serving as the omitted reference

period. The coefficients β_k trace the dynamic change in firm survival before and after fraud detection.

For the intensive margin, we focus on firms that are observed in Orbis and report non-missing values in a given year. We analyze the natural logarithm of total assets, number of employees, sales, and cost of goods sold. These outcomes are estimated on the unbalanced firm-year panel, since we do not impute zeros for missing firm-year observations and allow the set of firms contributing to each outcome to vary over time. We therefore estimate the following regression equation for firm i and year t :

$$\log(FirmOutcome_{it}) = \alpha_i + \sum_{k \neq -1} \beta_k \cdot Treatment_{it}^{(k)} + \lambda_t + \varepsilon_{it}. \quad (2)$$

The treatment indicators $Treatment_{it}^{(k)}$ capture event time relative to the relevant treatment event. Depending on the specification, treatment is defined either as the first EuroFisc audit or as the first year in which the firm is identified as a fraudster. As above, the event-time index k denotes the number of years before or after treatment, with $k = -1$ serving as the reference period. The coefficients β_k trace the dynamic effect of audits or fraud detection on firm performance.

Both specifications include firm fixed effects, α_i , and year fixed effects, λ_t . Firm fixed effects absorb time-invariant differences across firms, while year fixed effects account for common macroeconomic shocks. Standard errors are clustered at the firm level.

We distinguish four treatment settings. First, we estimate the effect of detected fraud on fraudulent firms. Second, we examine the effect of fraud detection on trade partners of fraudulent firms, which allows us to assess whether exporting firms adjust similarly to fraudulent firms, consistent with coordinated activity within trading relationships. Third, we estimate the effect of audits on audited firms irrespective of whether fraud is detected. Fourth, we analyze effects on trade partners of audited firms. In all specifications, the control group consists of firms operating in audited country-industries that have not yet

been audited.

5.2 Extensive-Margin: Survival Dynamics

We begin by examining the extensive-margin association of fraud detection and firm survival. In this setting, firm exit represents the most direct adjustment margin following audit activity. We focus on firms identified as fraudulent firms and missing traders, as well as their exporting trade partners. This allows us to assess whether fraud detection is followed by exits among the detected firms themselves and whether similar adjustments occur among connected firms within the trading network.

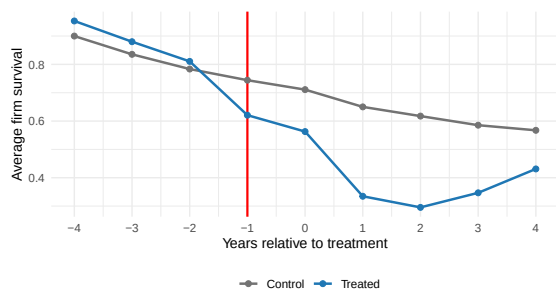
Figure 8 first provides descriptive evidence on survival dynamics around fraud and missing-trader detection. The raw averages show that treated firms experience a pronounced decline in survival after detection, whereas survival among the corresponding control firms remains comparatively stable. We then estimate dynamic DiD specifications to account for firm and year fixed effects and to assess whether treated and control firms follow similar pre-treatment trends. Figure 9 reports the corresponding event-study estimates. Across all panels, pre-treatment coefficients are small, supporting the parallel-trends assumption underlying our DiD design. Panel A shows a sharp decline in survival probabilities for fraudulent importing firms immediately after detection, with effects persisting in subsequent years. Panel C reveals a very similar pattern for missing traders. These results indicate that firms identified in fraud-related audits are substantially more likely to disappear after detection, consistent with the short-lived nature of firms involved in MTF schemes.

Panels B and D report the corresponding event-study estimates for exporting trade partners of fraudulent firms and missing traders. These trade partners also experience a decline in survival probabilities after the detection event, although the estimated effects are smaller than for the directly detected firms. Because these firms are not themselves recorded as the fraud-committing entities in EuroFisc, their subsequent exit suggests that fraud detection may reveal broader trading relationships connected to the fraudulent scheme.

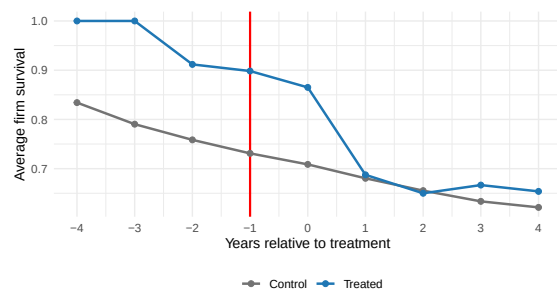
We interpret this pattern as suggestive evidence that, in some cases, exporting trade partners are not merely passive counterparties but may be involved in coordinated MTF trades.

The estimated effects for fraudulent firms and missing traders are large and also nearly identical, suggesting that the broader fraud category is largely driven by firms that exhibit the exit patterns characteristic of missing traders. Detection reduces the probability that a firm survives by about 39 percentage points in the first two years after treatment. For exporting trade partners, the estimated effects are smaller but still economically meaningful. Trade partners of fraudulent firms experience a 13 percentage-point reduction in survival after detection in the first two years after the fraud detection.

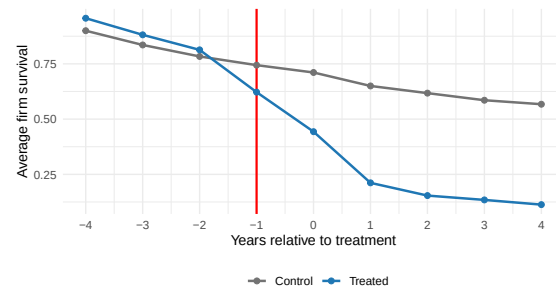
Figure 8: Firm Survival Raw Averages



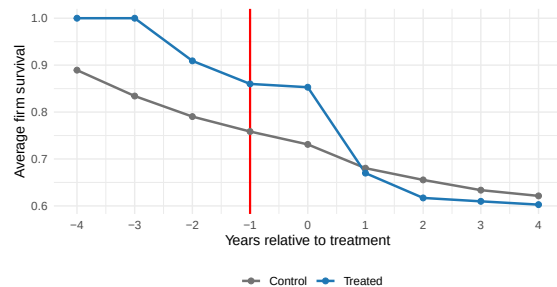
Panel A: Fraudulent Firm



Panel B: Trade Partner Fraudulent Firm



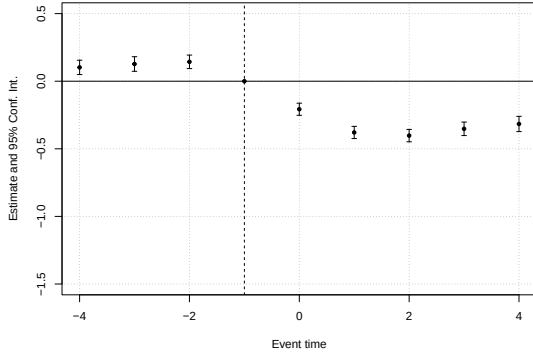
Panel C: Missing Trader



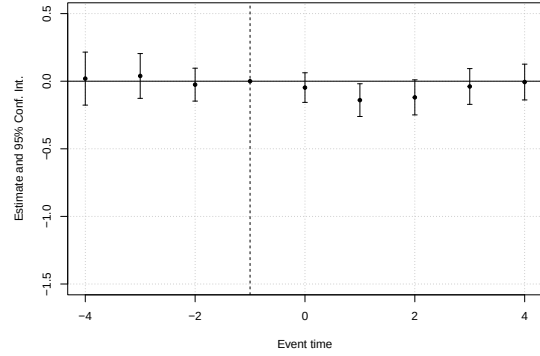
Panel D: Trade Partner Missing Trader

Notes: This figure presents the raw averages firm survival rates. The dependent variable is a firm survival indicator equal to one if the firm is observed in Orbis in a given year and zero otherwise. Panels A and C report effects for fraudulent firms and missing traders, respectively. Panels B and D report effects for trade partners of fraudulent firms and missing traders. The treatment indicators capture event time relative to the first fraud-detecting audit or missing trader audit. The red line marks the reference year $t = -1$.

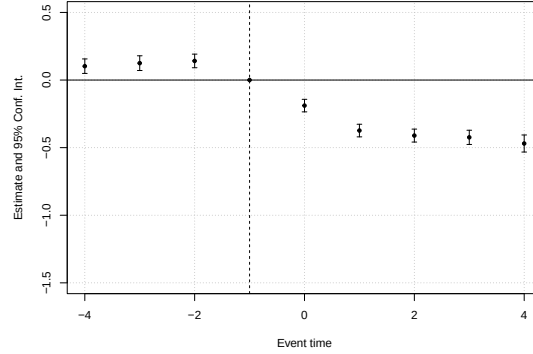
Figure 9: Firm Survival Around Fraud Detection



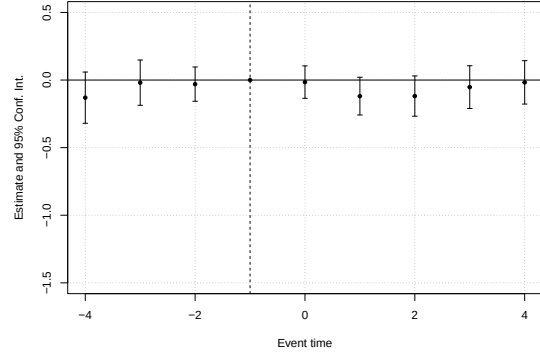
Panel A: Fraudulent Firm



Panel B: Trade Partner Fraudulent Firm



Panel C: Missing Trader



Panel D: Trade Partner Missing Trader

Notes: This figure presents dynamic DiD coefficients from estimating Equation 1 using LPM. The dependent variable is a firm survival indicator equal to one if the firm is observed in Orbis in a given year and zero otherwise. Panels A and C report effects for fraudulent firms and missing traders, respectively. Panels B and D report effects for trade partners of fraudulent firms and MT firms. The treatment indicators capture event time relative to the first fraud-detecting audit or missing trader audit. Firm and year fixed effects are included. Standard errors are clustered at the firm level. The black lines denote 95% confidence intervals. The dashed line marks the reference year $t = -1$.

5.3 Intensive-Margin: Firm Performance

We next examine how audits are associated with firm performance among surviving firms. This intensive-margin analysis differs from the survival analysis in two important respects. First, it is restricted to firms that survive and report non-missing outcome values. Second, the outcomes capture changes in reported economic activity rather than firm disappearance. Accordingly, the results describe the evolution of firm performance around fraud-detection and audit events. We interpret the following dynamic responses as descriptive

evidence on firm performance around enforcement events, rather than as causal year-by-year treatment effects.

Figure 10 presents the dynamic DiD estimates for fraudulent firms and their exporting trade partners. Panel A shows pronounced growth in total assets among fraudulent firms in the years leading up to fraud detection. Relative to the omitted year immediately before detection, total assets are about 73 percent lower four years before detection. Equivalently, they increase by about 265 percent between event years $t = -4$ and $t = -1$, corresponding to an annualized growth rate of roughly 54 percent.²² This pre-detection increase suggests that firms may be selected into audits partly because they experience unusually rapid growth or sharp changes in reported activity before detection. It may also reflect the build-up of fraudulent trading activity prior to the audit. After fraud detection, however, asset growth clearly flattens. Surviving fraudulent firms remain larger than before detection, but the steep upward trajectory observed in the pre-detection period does not continue.

Panel B shows a similar but more muted pattern for exporting trade partners of fraudsters. Their total assets are about 52 percent lower four years before their trading partner is detected than in the year immediately preceding detection. This corresponds to an increase of about 107 percent between event years $t = -4$ and $t = -1$, or an annualized growth rate of roughly 27 percent. After the detection event, the growth path flattens. This slowdown is consistent with a disruption of trading relationships once fraud is uncovered. It may reflect deterrence among trade partners involved in the fraudulent arrangement, who scale back activity after detection. Alternatively, it may capture responses by compliant trading partners, such as terminating contracts or reducing transactions with identified fraudsters.

We repeat the analysis for additional firm-performance outcomes: number of employees (Panel C and D), sales (Panel E and F), and cost of goods sold (Panel G and H). The pre-detection growth pattern documented for total assets is also visible for sales and cost of

²²The annual growth rate is calculated as the difference between the event-time coefficient in the omitted reference year, $\hat{\beta}-1 = 0$, and the coefficient in event year $t = -4$, divided by three years and exponentiated: $\exp((\hat{\beta}-1 - \hat{\beta}-4)/3) - 1$. With $\hat{\beta}-4 = -1.295$, this corresponds to $\exp(1.295/3) - 1 = 0.54$, or 54 percent per year.

goods sold. By contrast, we do not observe a comparable increase in employment before fraud detection. This suggests that firms involved in MTF expand mainly along financial or transactional margins, rather than through real employment growth. In line with the nature of MTF schemes, the observed increases in sales, costs, and assets may therefore reflect inflated transaction volumes or paper profits rather than genuine expansion in production capacity.

Figure A2 examines the evolution of total assets around EuroFisc audits, for firms where no fraud is detected. Panel A shows that audited firms also grow before the audit event, indicating that audit selection is generally related to prior firm expansion or changes in reported activity. However, the pre-audit growth of audited firms is substantially less pronounced than the growth observed for fraudulent firms in Figure 10. This comparison suggests that rapid pre-treatment expansion is present in the broader audit sample, but is much stronger among firms for which fraud is actually detected.

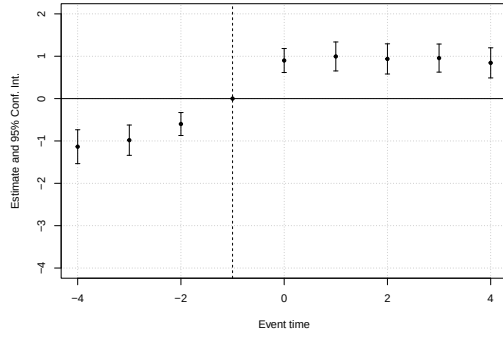
After the audit, the upward trajectory of audited firms no longer continues: asset growth flattens and remains broadly stable relative to the audit year. Panel B shows a similar pattern for exporting trade partners of audited firms. Trade partners of audited firms show a similar pattern as the audited firms themselves. The results for the effect of audits on the number of employees, sales and cost of goods sold can be found in the Appendix in Figure A2.

6 Reverse Charge Mechanism: Direct Effects and Displacement

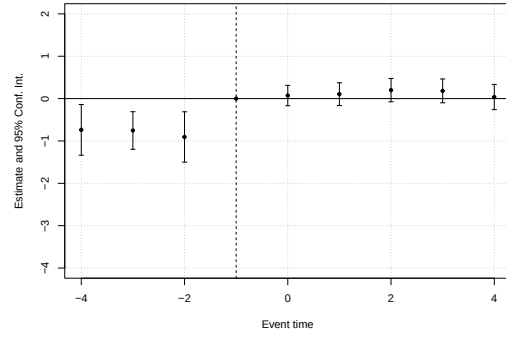
6.1 Empirical Strategy

To evaluate the effectiveness of the RCM in mitigating MTF fraud, we combine the EuroFisc data with hand-collected information on the timing and scope of RCM reforms

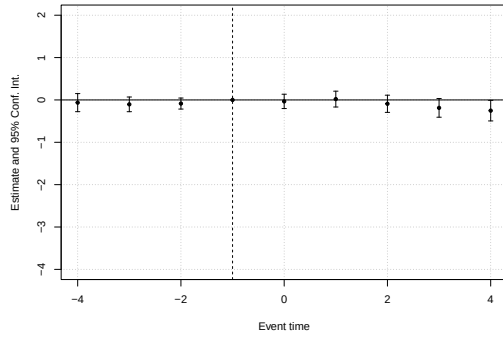
Figure 10: Dynamics of Fraud Detection on Firm Performance



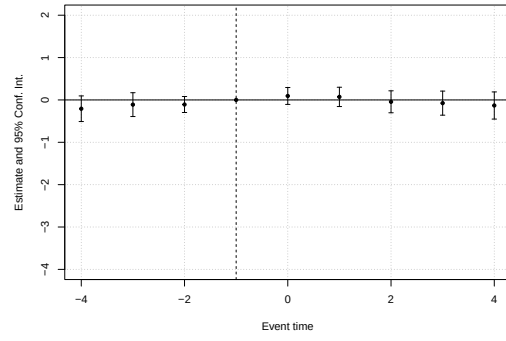
Panel A: Total assets, fraudulent firms



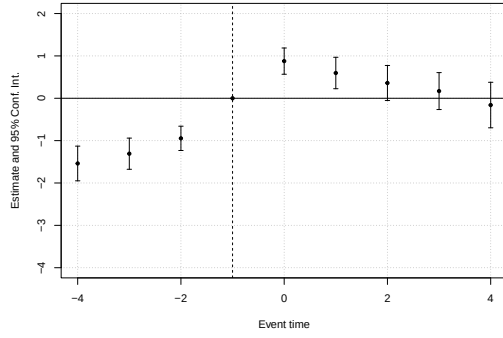
Panel B: Total assets, trade partners



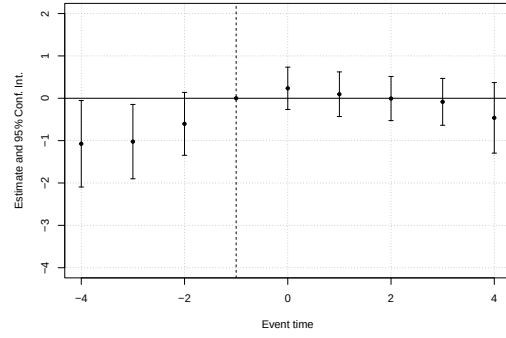
Panel C: Employment, fraudulent firms



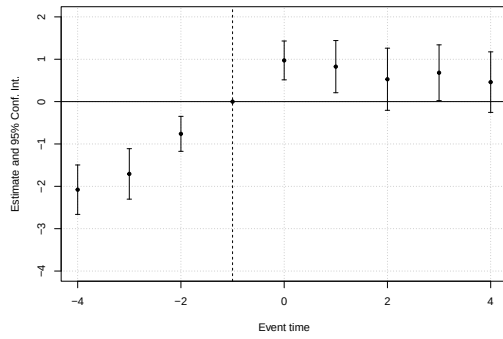
Panel D: Employment, trade partners



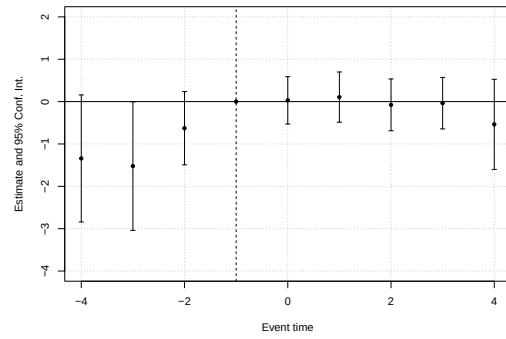
Panel E: Sales, fraudulent firms



Panel F: Sales, trade partners



Panel G: Cost of goods sold, fraudulent firms



Panel H: Cost of goods sold, trade partners

Notes: This figure presents dynamic DiD coefficients from estimating Equation 2 using OLS. The dependent variables are the logarithm of total assets, number of employees, sales, and cost of goods sold. The left column reports effects for fraudulent firms; the right column reports effects for their trade partners. Firm and year fixed effects are included. Standard errors are clustered at the firm level. The black lines denote 95% confidence intervals. The dashed line marks the reference year $t = -1$.

across all 28 EU Member States.²³

Using country-specific legislation and European Commission reports, we collect information on the introduction dates and product coverage of domestic RCM reforms. We then map these reforms to country-industries using NACE-4 classifications. More specifically, industries are classified as treated once they operate in product categories subject to the RCM in a given country and year. Based on these country-industry mappings, we construct a balanced country-industry and year panel covering all audited country-industries observed in the EuroFisc data. This procedure generates differential treatment variation across industries, countries, and time, allowing us to compare changes in audit activity and detected fraud between treated and untreated country-industries. The full sample selection is depicted in Panel C of Table A1.

The final panel consists of country-industry observations from 2012 to 2018. We use this panel to analyse the impact of the RCM on audit activity and detected cross-border MTF. The treatment group comprises country-industries exposed to RCM reforms, while the control group consists of country-industries without RCM exposure in the respective year. Outcomes are aggregated at the country-industry-year level based on the importing firm's industry code in the EuroFisc data. Specifically, we aggregate both the volume and the number of audits, detected fraud cases, and detected fraud cases involving a missing trader.

Table A3 reports summary statistics for the RCM panel. Country-industries that adopt the RCM exhibit substantially higher audit intensity and fraud levels than untreated country-industries. For example, the average number of audits amounts to 20.29 in treated country-industries compared to 4.79 in the control group. Similarly, the average fraud volume amounts to EUR 546 thousand in treated country-industries compared to EUR 116 thousand among controls. Treated country-industries also display higher average amount of missing trader fraud volume throughout the sample period. These differences suggest that RCM reforms are primarily introduced in industries already characterised by elevated fraud risks

²³The United Kingdom is included since it was still part of the EU during the observation period from 2012 to 2018.

and audit intensity.

Given that RCM regimes are introduced at different points in time across countries and industries, we employ a staggered DiD approach. We estimate the following event study specification using poisson pseudo maximum likelihood (PPML), depending on the outcome variable. Recent econometric evidence shows that PPML estimators are particularly well suited for outcome variables that are nonlinear, contain a large share of zero observations, or are defined on the non-negative domain (Chen and Roth 2023; Wooldridge 2023). In contrast to log linearized OLS specifications, PPML allows estimation in levels without requiring log transformations and remains consistent under general forms of heteroskedasticity. This is particularly relevant in our setting, where most outcome variables have a median value of zero (see Table A3).

Our baseline specification estimates the effect at the country–industry (c,i) and year (t) level:

$$AuditFraudIntensity_{cit} = \alpha_{ci} + \sum_{k \neq -1} \beta_k \cdot RCM_{cit}^{(k)} + \lambda_t + \varepsilon_{cit} \quad (3)$$

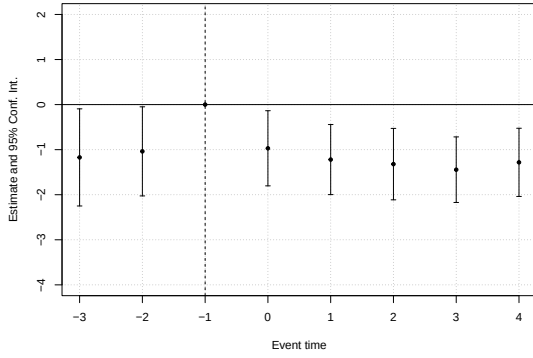
where $AuditFraudIntensity_{cit}$ denotes either the volume or number of audited, fraudulent or specifically missing trader transactions. The treatment group consists of industry sectors subject to RCM at the country–NACE-4 level, while non-RCM sectors form the control group. $RCM_{cit}^{(k)}$ equals 1 if country–industry (c,i) is k years away from the introduction of the RCM regime at time t , and 0 otherwise. The coefficients β_k capture the year-by-year effect of the RCM relative to the reference period. We include fixed effects for country–industry pairs and years to account for time-invariant sectoral characteristics and common shocks.

6.2 Direct Effects in Treated Country-Industries

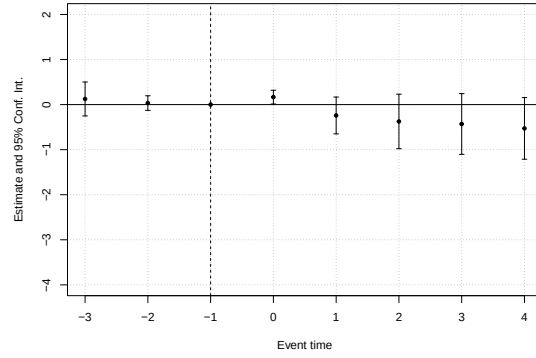
We start by providing graphical evidence on the effect of the RCM on audit and detected fraud intensity by estimating a dynamic specification of Equation 3 that allows the dynamics of RCM introduction over time relative to its introduction. Specifically, instead of a single treatment indicator, we define a set of event-time indicators for each year before and after the RCM implementation.

Figure 11 presents the dynamics of RCM implementation in treated sectors for all six outcome variables. Panels A and B show the association with audit activity, measured by audit volume and the number of audits, respectively. Panels C and D report the corresponding interactions with detected fraud volume and the number of fraud cases, while Panels E and F focus specifically on MTF volume and the number of missing trader cases. Across all panels, the pre-treatment coefficients are close to zero and show no systematic pretrend, suggesting that treated and control sectors followed similar trajectories prior to RCM implementation. This supports the parallel trends assumption. After treatment, the coefficients turn negative and are statistically significant across the outcomes. The decline in audit volume and audit counts suggests that tax authorities may reallocate enforcement resources away from sectors covered by the RCM. At the same time, the significant reductions in both the volume and number of detected fraud cases, including missing trader fraud, indicate that the RCM is associated with a decline in cross-border fraud activity in treated industries.

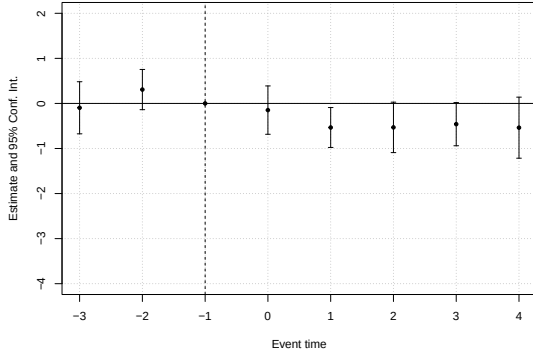
Figure 11: Direct Effects of RCM in Treated Country-Industries



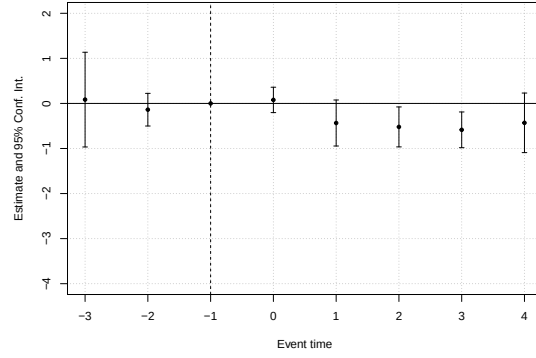
Panel A: Audit Volume



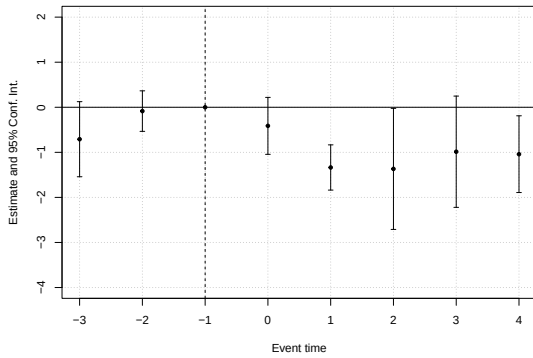
Panel B: Number of Audits



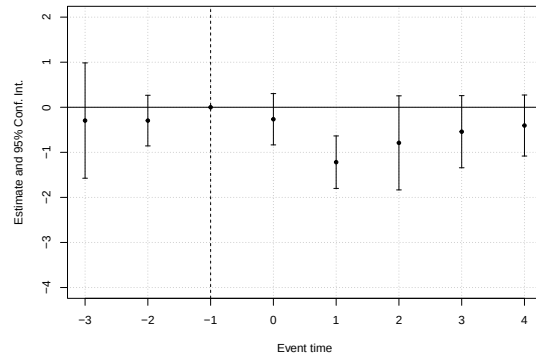
Panel C: Fraud Volume



Panel D: Number of Fraud Cases



Panel E: Missing Trader Volume



Panel F: Number of Missing Traders

Notes: This figure presents dynamic DiD coefficients from estimating Equation 3 using PPML. The dependent variables are audit volume (Panel A), number of audits (Panel B), fraud volume (Panel C), number of detected fraud cases (Panel D), missing trader volume (Panel E), and the number of detected missing traders (Panel F). The treatment indicators capture event time relative to the first RCM introduction in a country-industry. Country-industry and quarter-year fixed effects are included. Standard errors are clustered at the country-industry level. The black lines denote 95% confidence intervals. The dashed line marks the reference year $t = -1$.

Panel A of Table 5 presents the corresponding regression results on the association between RCM implementation, audit activity, and detected MTF. All regressions include country-industry and year fixed effects, and standard errors are clustered at the country-industry level. The reported coefficients correspond to the treatment indicator for RCM implementation. Columns 1 and 2 report results for audit activity. RCM implementation is associated with a significant decline in audit volume of approximately 55 percent, while the number of audits does not decrease significantly. For detected fraud, we observe a reduction of around 43 percent in fraud volume and 24 percent in the number of fraudulent transactions. The association with missing trader activity is even more pronounced, with reductions of 56 percent in volume and 36 percent in the number of cases.

The results indicate that the implementation of the RCM is associated with lower audit intensity and reduced detected fraud in treated country-industries. This pattern is consistent with tax authorities reallocating enforcement resources away from sectors covered by the RCM, where opportunities for MTF are substantially reduced. At the same time, the estimated effects likely represent lower-bound estimates of the true impact of the RCM. Since the treatment is defined at the country-industry level, the data do not allow us to separately identify fraud displacement or spillovers across products within treated sectors. Consequently, remaining fraud activity within the same country-industry may attenuate the estimated reduction in fraud outcomes.

6.3 Spillovers to Untreated Country-Industries

In the next step, we examine spillover effects of RCM implementation on non-treated but related country-industries. We define a NACE-4 country-industry as related to an RCM-treated industry in two cases. First, if it belongs to the same NACE-2 industry in the same country but is not itself subject to the RCM. Second, if it corresponds to the same NACE-4 industry in another country that has not implemented the RCM for that industry.

We then analyse audit activity and detected fraud in these related industries after RCM

introduction. The expected association with audit activity is ambiguous. Tax authorities may redirect enforcement toward related sectors, but it is unclear whether standard audits and RCM-related inspections are treated as substitutes, or whether overall audit resources adjust after implementation. For fraud outcomes, however, we expect positive spillovers. If firms engage in MTF to generate illicit funds or launder money, they may shift activity toward closely related industries or establish new firms in countries where the relevant industry is not covered by the RCM.

Figure 12 presents the dynamic spillovers of the RCM on related industries. We find no clear evidence of changes in either the volume or the number of audits in related industries following RCM implementation in Panels A and B. By contrast, we observe positive and statistically significant spillovers in detected fraud intensity. The effects are visible for fraud volume (Panel C) and the number of fraud cases (Panel D), and are even more pronounced for the volume and number of MTF cases (Panels E and F).

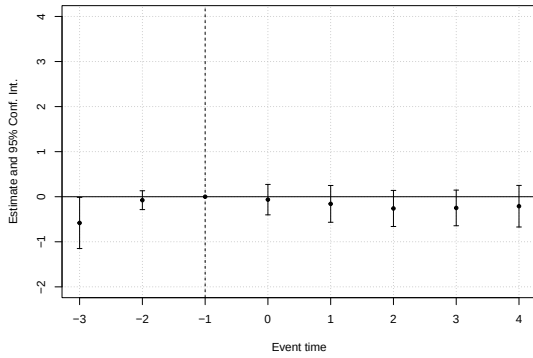
Panel B of Table 5 reports the corresponding regression estimates. All regressions include country-industry and year fixed effects, and standard errors are clustered at the country-industry level. The reported coefficients correspond to an indicator for post-RCM exposure in related but non-treated industries. Columns 1 and 2 report audit outcomes. We find no statistically significant association with audit volume (Column 1), while the number of audits in related industries is positively associated with spillover exposure (Column 2). This pattern suggests that related industries experience a modest increase in audit frequency, although this is not accompanied by a corresponding increase in total audited volume. Columns 3 to 6 report results for detected fraud outcomes in related, non-treated industries. The point estimates are positive across all fraud outcomes. The association is statistically significant for fraud volume (Column 3) and for the number of missing trader cases (Column 6), while the estimates for the number of fraud cases and missing trader volume are positive but less precisely estimated. The coefficient for fraud volume corresponds to an economically substantive increase of approximately 59 percent, and the coefficient for

the number of missing trader cases corresponds to an even larger increase of approximately 69 percent.

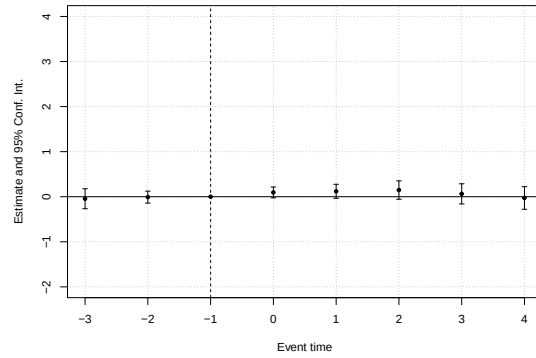
Panel C of Table 5 focuses specifically on the cross-country component of these spillovers. The estimates show that the positive fraud spillovers are particularly pronounced for country-industries exposed through RCM implementation in the same NACE-4 industry abroad. The coefficients are large and statistically significant for fraud volume and the number of fraud cases, and also positive for missing trader outcomes. This suggests that the combined spillover effects are not only driven by shifts to related industries within the same country, but especially by cross-border displacement toward countries where the same industry remains outside the RCM. Panel D of Table 5 examines within-industry spillovers within treated countries. Specifically, it considers untreated NACE-4 industries that belong to the same broader NACE-2 sector as an RCM-treated industry. The estimates provide some evidence of within-country displacement. While audit activity remains largely unchanged, fraud volume increases significantly and the number of missing trader cases also rises. These findings suggest that fraudsters may partially reallocate their activities toward closely related product categories that remain outside the scope of the RCM. However, these effects are smaller and less precisely estimated than the cross-country spillovers documented in Panel C, indicating that cross-border relocation appears to be the more important margin of adjustment.

The positive coefficients for detected fraud outcomes are consistent with spillovers to related industries after RCM implementation. These spillovers occur without a corresponding increase in audit volume, suggesting that the higher detected fraud is not simply driven by a larger audited transaction volume in related industries. In combination with the baseline results for treated industries, this pattern is consistent with a shift in detected fraud from treated to related industries. At the same time, the estimates do not allow us to distinguish whether this reflects a change in underlying fraudulent activity, changes in detection, or both.

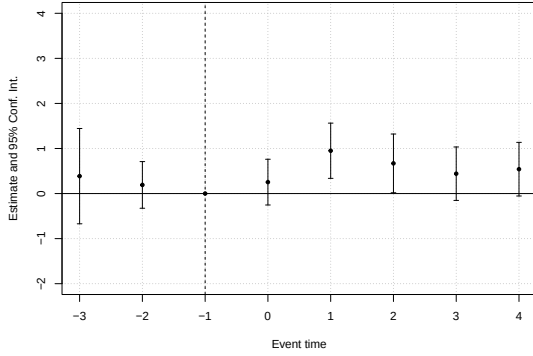
Figure 12: Spillover Effects of RCM in Un-treated Country-Industries



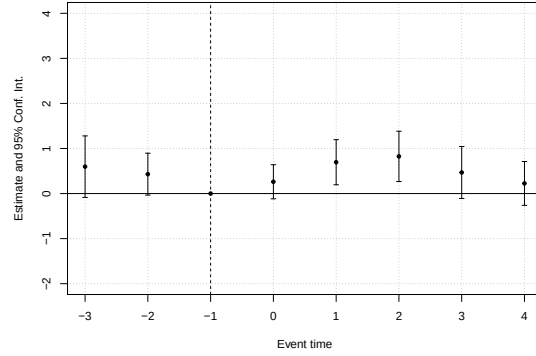
Panel A: Audit Volume



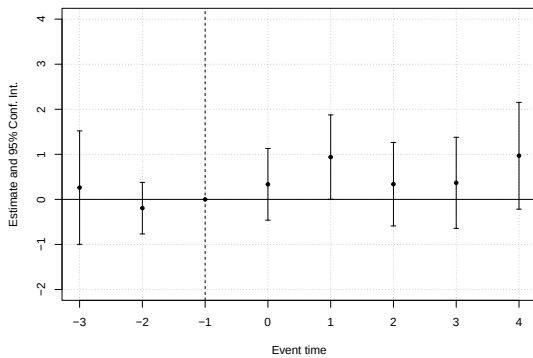
Panel B: Number of Audits



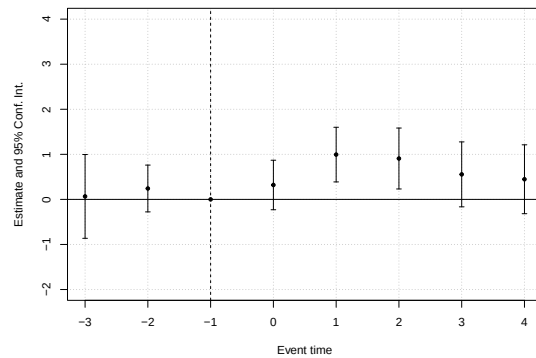
Panel C: Fraud Volume



Panel D: Number of Fraud Cases



Panel E: Missing Trader Volume



Panel F: Number of Missing Traders

Notes: This figure presents dynamic DiD coefficients from estimating spillovers following the introduction of the RCM. Spillover industries are defined in two ways: first, as untreated NACE-4 industries within the same country that share the same NACE-2 sector with an RCM-treated industry, and second, as the same NACE-4 industries located in countries that did not implement the RCM. The dependent variables are audit volume (Panel A), number of audits (Panel B), fraud volume (Panel C), number of detected fraud cases (Panel D), missing trader volume (Panel E), and the number of detected missing traders (Panel F). The treatment indicators capture event time relative to spillover exposure from RCM implementation in a country-industry. Country-industry and quarter-year fixed effects are included. Standard errors are clustered at the country-industry level. The black lines denote 95% confidence intervals. The dashed line marks the reference year $t = -1$.

Table 5: Direct and Displacement Effects of RCM

	Audits		Fraud		Missing Trader	Fraud
	Volume	Number	Volume	Number	Volume	Number
Panel A: Direct Effects in Treated Country-Industries						
Post x RCM	-0.8049*** (0.3016)	-0.1492 (0.1477)	-0.5603*** (0.1517)	-0.2808** (0.1312)	-0.8278*** (0.2184)	-0.4478* (0.2498)
Observations	31,010	43,729	4,529	5,152	3,997	4,599
Pseudo R^2	0.59	0.80	0.71	0.75	0.65	0.71
Panel B: Spillover Effects in Untreated Country-Industries						
Post x Spillover	-0.0841 (0.1793)	0.1143* (0.0666)	0.4647* (0.2509)	0.3137 (0.1998)	0.5448 (0.3535)	0.5265** (0.2620)
Observations	29,134	41,440	4,165	4,767	3,689	4,263
Pseudo R^2	0.64	0.82	0.72	0.74	0.66	0.73
Panel C: Spillover Effects in Untreated Cross-Country-Industries						
Post x Cross-Country Spillover	-0.4631* (0.2660)	-0.0500 (0.1451)	0.8572*** (0.3276)	0.8186*** (0.3164)	1.0520* (0.5810)	0.2933 (0.5162)
Observations	29,134	41,440	4,165	4,767	3,689	4,263
Pseudo R^2	0.63	0.82	0.72	0.76	0.64	0.70
Panel D: Within-Industry Spillover Effects						
Post x Within-Industry Spillover	-0.0390 (0.1975)	0.1365** (0.0694)	0.4374* (0.2475)	0.2403 (0.2001)	0.4861 (0.3589)	0.5022* (0.2646)
Observations	29,608	42,029	4,233	4,843	3,733	4,317
Pseudo R^2	0.62	0.84	0.72	0.75	0.67	0.74

Notes: This table reports estimates from staggered DiD regressions from estimating Equation 3 using PPML. The treatment variable equals one for country-industries exposed to RCM in the post-treatment period and zero otherwise. In Panel B, spillover industries are defined in two ways: first, as untreated NACE-4 industries within the same country that share the same NACE-2 sector with an RCM-treated industry, and second, as the same NACE-4 industries located in countries that did not implement the RCM. In Panel C, spillover industries are defined as NACE-4 industries that are subject to RCM in a country, but located in countries that did not implement the RCM. Panel D defines spillover industries as untreated NACE-4 industries within the same country that share the same NACE-2 sector with an RCM-treated industry. All specifications include country-industry and year fixed effects. Standard errors are clustered at the country-industry level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

6.4 Net Deterrence of Reverse Charge

The estimates above show that RCM reforms reduce detected fraud in treated country-sectors but increase detected fraud in related untreated jurisdictions. To assess the net deterrence effects these reforms, we conduct a simple accounting exercise that compares the direct reduction in detected fraud in treated sectors with the increase in detected fraud in spillover cells.

For each margin m , where m denotes either treated sectors or spillover cells, we convert

Table 6: Offsetting Effects of RCM Spillovers

Margin	$\hat{\beta}^F$	$\bar{F}$	ΔF	Offset ratio
Direct effect in treated sectors	-0.5603	855.13	-366.820	—
Spillover effect across countries	0.8572	188.78	256.100	0.698

the estimated PPML coefficients into proportional effects using $\exp(\hat{\beta}) - 1$. Let F_m denote detected fraud. The implied change in detected fraud is

$$\Delta F_m = \left(\exp(\hat{\beta}_m^F) - 1 \right) \bar{F}_m.$$

The offset ratio is defined as the value of spillover effect divided by the value of the direct effect in treated sectors:

$$\text{Offset Ratio} = \frac{\Delta F_{\text{spillover}}}{|\Delta F_{\text{treated}}|}.$$

As shown in Table 6, the displacement effect is economically large. The cross-country spillover effect offsets 70 percent of the direct reduction in detected fraud in treated sectors. Defining spillovers as the combination of increases in fraud in related untreated sectors within the implementing country and in the same NACE-4 sector in Member States that did not adopt RCM would increase this effect even further. As discussed above, we do not find any evidence that tax authorities reallocate audits toward untreated sectors or jurisdictions after RCM adoption, which could potentially explain the increase in fraud. If anything, audit volumes even decrease, which would, again, further increase the offsetting effect that we find.

7 Conclusion

We show that, despite the large fiscal importance of missing trader VAT fraud in the EU, existing approaches are unlikely to capture this fraud accurately. Mirror-trade measures miss a large share of fraudulent transactions because many detected fraudulent

trades fall below intra-EU reporting thresholds. Estimates based on RCM reforms face a different problem: they infer fraud from reforms that close treated transaction channels, but generally do not account for displacement across products and jurisdictions. As a result, firm- and sector-level estimates may overstate the amount of fraud eliminated by RCM, while country-level estimates may understate the underlying fraud if displacement occurs within the EU.

Our audit data provide direct evidence on the revealed anatomy of detected MTF. Detected fraud is highly concentrated geographically, sectorally, and across firm types. Missing traders are disproportionately located in the Baltics, Eastern Europe, and Southern Europe, while broker counterparties are more often located in Western Europe. Sectorally, detected fraud is concentrated in wholesale and retail trade, especially in chemicals, ICT equipment, and household goods. At the firm level, missing traders are typically micro firms transacting unusually large volumes relative to their size, whereas brokers are larger and often appear to combine legitimate business with MTF-related activity. The transaction data further show that detected schemes are embedded in repeated multi-firm and multi-country trading networks rather than isolated bilateral transactions. These patterns should be interpreted as evidence on detected fraud, not the universe of MTF, since audit targeting and reporting strategies may differ across Member States.

The evidence also informs the relative strengths and limits of the two main counter-measures against MTF. Detection is followed by sharp exit among missing traders and by a break in the rapid pre-detection growth of surviving firms, with similar but smaller dynamics among exporting trade partners. This suggests that audits can reveal and disrupt parts of the trading networks through which MTF operates. RCM reforms, in contrast, mechanically reduce audit activity and detected fraud in treated sectors, but also induce substantial cross-country displacement to similar sectors in Member States that did not adopt RCM. We estimate that this displacement offsets most of the direct deterrence effect. The central policy implication is therefore not that one instrument dominates the other, but

that effective anti-fraud policy must account for the networked and mobile nature of MTF. Product-specific reforms can close particular channels, while targeted audits can disrupt detected nodes and links; designing policy requires understanding how these instruments interact when fraudsters can reorganize across firms, sectors, and borders.

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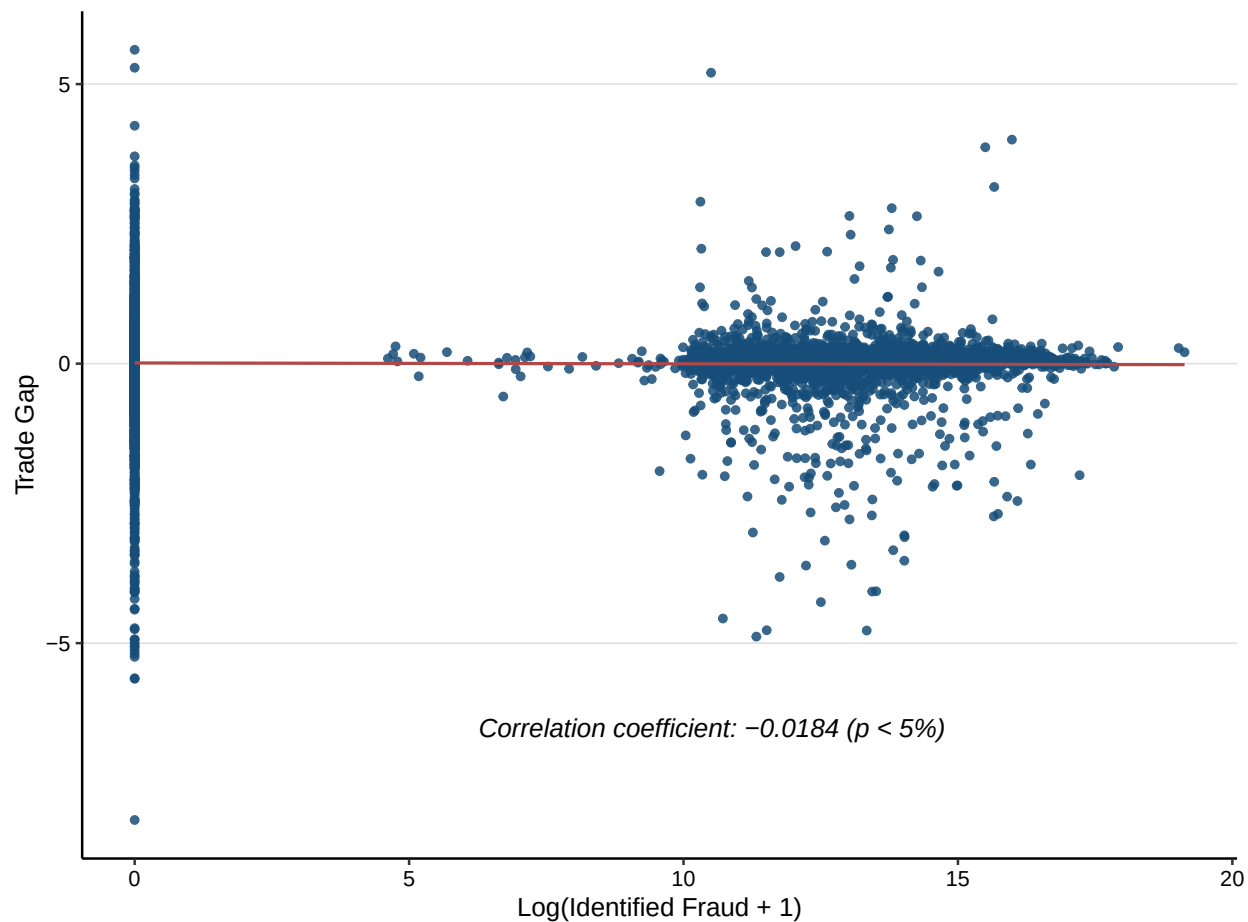
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8 Appendix

Figure A1: Correlation of Trade Gaps with Detected Fraud



Notes: This figure plots total trade gaps against detected fraud at the exporter-importer-quarter level. The trade gap is defined as the logarithm of exports reported by the exporting country relative to imports reported by the importing country. Detected fraud is measured as the logarithm of one plus the value of fraudulent transactions identified in the EuroFisc data for the corresponding country pair and quarter. The red line shows the linear fit. The correlation coefficient and its p-value are reported in the figure.

Table A1: Sample Construction and Selection

Sample	Selection step	Observations	Units/Firms
<i>Panel A: EuroFisc Sample</i>			
EuroFisc transactions	Raw appended transaction data	565,453	
EuroFisc transactions	Drop intra-country or missing-country transactions	565,431	
EuroFisc transactions	Drop negative transactions	565,063	
EuroFisc transactions	Drop duplicate transaction records	388,933	
EuroFisc transactions	Final cleaned incoming-cross transaction sample	388,933	68,890
Final EuroFisc sample	Add VAT-ID and Orbis industry information	286,588	68,890
Final EuroFisc sample	Drop transactions without year information	284,947	68,741
<i>Panel B: Orbis Samples</i>			
Orbis financials	Firm-year financial panel after country, account-type, reporting-period, firm-year, core-financial, and plausibility restrictions	60,844,223	14,488,390
Orbis audit sample	Orbis firms matched to audited EuroFisc importing firms	181,027	32,355
Orbis audit sample	Assign missing treated-firm industries and build country-NACE-4 comparison sample around audited importing firms	22,304,142	5,056,392
Orbis detected fraud sample	Orbis firms matched to fraudulent EuroFisc importing firms	2,734	787
Orbis detected fraud sample	Assign missing treated-firm industries and build country-NACE-4 comparison sample around fraudulent importing firms	4,223,777	956,038
Orbis detected fraud firm-exit sample	Assigned country-NACE-4 comparison sample around fraudulent importing firms, balanced from each firm's first Orbis observation within 2012–2019 onward	6,186,954	956,038
<i>Panel C: RCM Sample</i>			
RCM sample	Final EuroFisc transaction sample	284,947	68,741
RCM sample	Restrict to the industry-analysis window before 2019	280,883	66,733
RCM sample	Keep transactions with importing-country and NACE information	261,796	62,690
RCM sample	Observed country-industry-year cells before balancing	18,539	6,621
RCM sample	Balanced country-industry-year panel	46,347	6,621

Notes: Panel A reports the construction of the EuroFisc transaction sample. Units in Panel A are distinct VAT identifiers observed on either side of a transaction. Panel B reports the construction of the Orbis importing-firm and firm-exit samples. For treated EuroFisc firms without observed Orbis industry information, we assign NACE-4 code 4651, wholesale of computers, computer peripheral equipment and software, before constructing the country-industry comparison samples. Units in Panel B are distinct Orbis firms identified by BvD identifiers. Panel C reports the construction of the NACE-level RCM industry panel. Observed cells are country-industry-year combinations before balancing. Balanced-panel observations are country-industry-year cells after completing the panel over the analysis window.

Table A2: Summary Statistics: Firm-Level Samples

	Control						Treatment					
	N	Mean	SD	Median	Min	Max	N	Mean	SD	Median	Min	Max
Panel A:	Firm Survival Sample											
Firm survival	6,181,821	0.68	0.47	1.00	0.00	1.00	5,133	0.53	0.50	1.00	0.00	1.00
Panel B:	Detected Fraud Sample											
Total assets (Mio. EUR)	4,074,414	1.52	5.30	0.23	0.00	53.32	2,643	5.11	11.80	0.57	0.00	53.32
Number of employees	2,280,040	9.65	22.77	3.00	0.00	196.00	1,958	16.85	39.10	3.00	0.00	196.00
Operating revenue (Mio. EUR)	4,060,830	1.36	4.70	0.18	0.00	41.84	2,471	8.09	13.55	1.01	0.00	41.84
Sales (Mio. EUR)	4,001,553	1.28	4.17	0.17	0.00	34.25	2,394	7.40	11.67	1.09	0.00	34.25
Cost of goods sold (Mio. EUR)	2,371,225	0.89	3.77	0.03	0.00	37.22	1,510	8.56	12.89	1.58	0.00	37.22
Panel C:	Audit Sample											
Total assets (Mio. EUR)	21,517,601	1.69	6.12	0.20	0.00	53.32	177,300	10.95	17.69	1.84	0.00	53.32
Number of employees	14,414,132	9.88	24.81	3.00	0.00	196.00	144,773	45.33	65.24	12.00	0.00	196.00
Operating revenue (Mio. EUR)	19,674,571	1.40	5.03	0.15	0.00	41.84	157,372	13.11	16.33	3.75	0.00	41.84
Sales (Mio. EUR)	19,068,417	1.32	4.44	0.14	0.00	34.25	154,052	11.46	13.63	3.69	0.00	34.25
Cost of goods sold (Mio. EUR)	8,942,322	0.95	4.10	0.04	0.00	37.22	88,095	11.37	14.54	2.95	0.00	37.22

Notes: This table reports summary statistics for the firm-level samples after merging EuroFisc with Orbis. Panel A reports the firm survival sample used to analyse the extensive margin effects. Panel B reports the detected fraud sample. The treatment group consists of audited firms identified as fraudsters. The control group consists of non-audited firms operating in country-industries in which at least one fraudster is detected. Panel C reports the audit sample. The treatment group consists of audited firms, while the control group consists of non-audited firms operating in the same country-industries.

Table A3: Summary Statistics: RCM Country-Industry Panel

	N	Mean	SD	Median	Min	Max
Panel A:		Treatment				
Audit Volume (EUR)	2,562	3,259,932.90	22,362,291.14	0.00	0.00	844,246,310.00
Number of Audits	2,562	20.29	105.23	1.00	0.00	2,843.00
Fraud Volume (EUR)	2,562	545,794.57	4,632,970.39	0.00	0.00	105,736,821.49
Number of Fraud Cases	2,562	2.86	22.20	0.00	0.00	629.00
Missing Trader Volume (EUR)	2,562	271,010.79	2,625,952.21	0.00	0.00	63,921,392.99
Number of Missing Trader Cases	2,562	1.43	12.90	0.00	0.00	347.00
Panel B:		Control				
Audit Volume (EUR)	43,785	712,910.21	6,083,394.72	0.00	0.00	362,176,732.47
Number of Audits	43,785	4.79	29.61	0.00	0.00	1,909.00
Fraud Volume (EUR)	43,785	116,141.45	2,122,204.24	0.00	0.00	199,946,405.03
Number of Fraud Cases	43,785	0.57	8.30	0.00	0.00	629.00
Missing Trader Volume (EUR)	43,785	54,204.83	908,323.85	0.00	0.00	77,880,739.00
Number of Missing Trader Cases	43,785	0.27	3.91	0.00	0.00	357.00

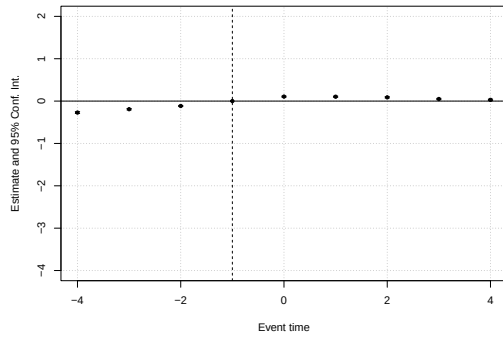
Note: This table reports summary statistics for the yearly country-industry panel used in the RCM analysis. The treatment group in Panel A consists of country-industries exposed to the RCM over the observation period from 2012 to 2018. The control group in Panel B consists of country-industries without RCM exposure.

Table A4: RCM Adoption by Member State and Legal Category (as of 31 December 2018)

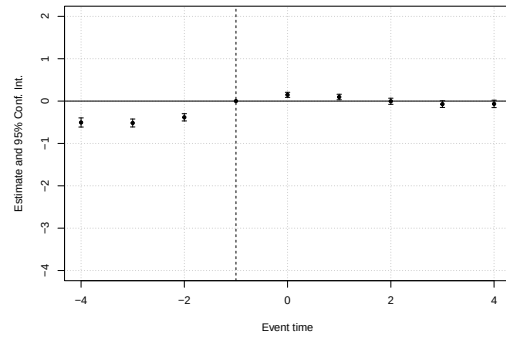
Member State	Legal category									
	Art. 199(1)(a)	Art. 199(1)(d)	Art. 199a(1)(c)	Art. 199a(1)(d)	Art. 199a(1)(e)	Art. 199a(1)(f)	Art. 199a(1)(g)	Art. 199a(1)(h)	Art. 199a(1)(i)	Art. 199a(1)(j)
Austria	-	-	2014	2014	2014	2014	-	2014	-	2014
Bulgaria	-	-	-	-	-	-	-	-	2014	-
Cyprus	2012	-	-	-	-	-	-	-	-	-
Czech Republic	2012	-	2015	2015	2016	2016	2017	2015	2015	2015
Germany	-	-	-	-	2013	-	-	2014	-	2014
Denmark	-	2012	2014	2014	2015	2015	-	2014	-	-
Estonia	-	-	-	-	-	-	-	-	-	2014
Greece	2014	-	2017	-	-	-	-	2017	-	-
Spain	-	-	2015	-	-	-	-	2015	-	2015
Finland	-	2015	-	-	-	-	-	-	-	-
France	2014	-	-	-	-	-	2015	-	-	-
United Kingdom	-	-	2014	2014	2014	-	2016	-	-	-
Croatia	2013	2013	-	-	-	-	-	-	-	-
Hungary	-	-	-	-	-	-	-	-	2014	2015
Ireland	-	-	-	-	2016	2016	-	-	-	-
Italy	-	-	2014	2014	2015	2015	-	2016	-	-
Lithuania	2015	-	-	-	-	-	-	-	-	-
Latvia	2012	-	2016	2016	-	-	-	2016	2016	2017
Netherlands	-	-	2013	2013	-	-	-	2013	-	-
Poland	2017	-	2015	2017	-	-	-	2015	-	2015
Romania	-	-	2016	2016	2013	2013	-	2016	-	-
Sweden	-	2013	-	-	-	-	-	-	-	-
Slovakia	2016	-	2014	2014	-	-	-	-	2014	2014

Notes: This table reports the first year of implementation of the RCM regimes in an EU Member State. A dash indicates that no implementation was recorded by 31 December 2018.

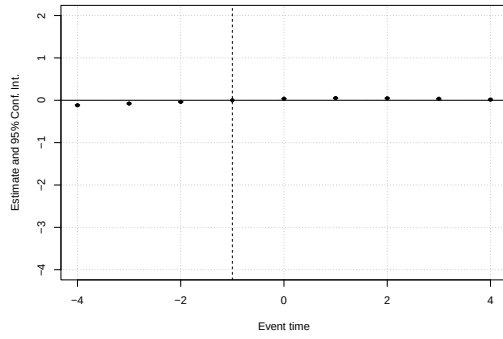
Figure A2: Dynamic Effects of Audits on Firm Performance



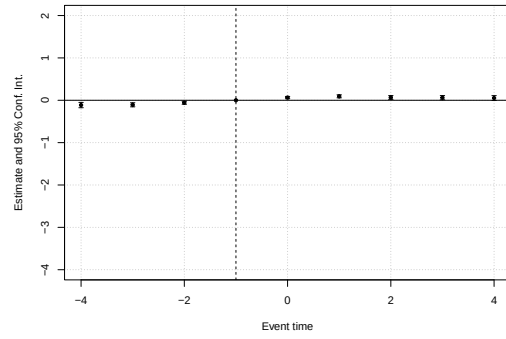
Panel A: Total assets, audited firms



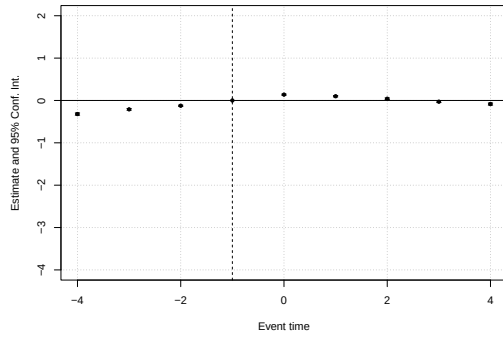
Panel B: Total assets, trade partners



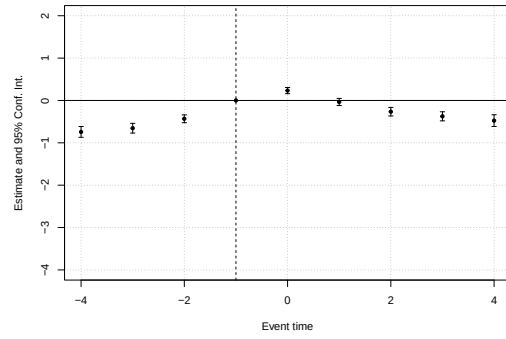
Panel C: Employment, audited firms



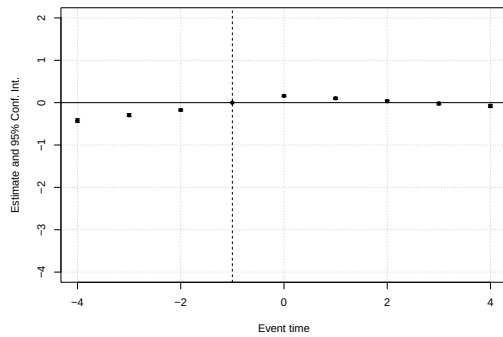
Panel D: Employment, trade partners



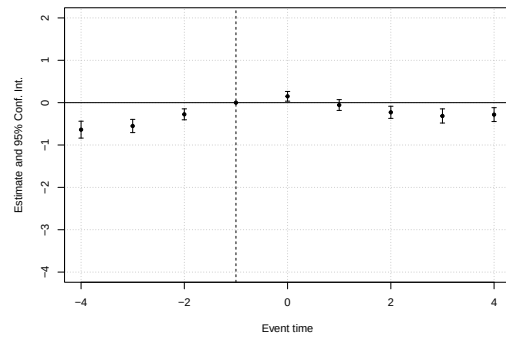
Panel E: Sales, audited firms



Panel F: Sales, trade partners



Panel G: Cost of goods sold, audited firms



Panel H: Cost of goods sold, trade partners

Notes: This figure presents dynamic DiD coefficients from estimating Equation 2 using OLS. The dependent variables are the logarithm of total assets, number of employees, sales, and cost of goods sold. The left column reports effects for audited but not fraudulent firms; the right column reports effects for their trade partners. Firm and year fixed effects are included. Standard errors are clustered at the firm level. The black lines denote 95% confidence intervals. The dashed line marks the reference year $t = -1$.