BANCA D'ITALIA
EUROSISTEMA

Mercati, infrastrutture, sistemi di pagamento

(Markets, Infrastructures, Payment Systems)

Modelling transition risk-adjusted probability of default

by Manuel Cugliari, Alessandra Iannamorelli and Federica Vassalli

May 2025

Number 59

BANCA D'ITALIA
EUROSISTEMA

Mercati, infrastrutture, sistemi di pagamento

(Markets, Infrastructures, Payment Systems)

Modelling transition risk-adjusted probability of default

by Manuel Cugliari, Alessandra Iannamorelli and Federica Vassalli

Number 59 – May 2025

The papers published in the 'Markets, Infrastructures, Payment Systems' series provide information and analysis on aspects regarding the institutional duties of the Bank of Italy in relation to the monitoring of financial markets and payment systems and the development and management of the corresponding infrastructures in order to foster a better understanding of these issues and stimulate discussion among institutions, economic actors and citizens.

The views expressed in the papers are those of the authors and do not necessarily reflect those of the Bank of Italy.

The series is available online at www.bancaditalia.it.

Printed copies can be requested from the Paolo Baffi Library: richieste.pubblicazioni@bancaditalia.it.

ISSN 2724-6418 (online)
ISSN 2724-640X (print)

Banca d'Italia
Via Nazionale, 91 - 00184 Rome - Italy
+39 06 47921

Designed and printing by the Printing and Publishing Division of the Bank of Italy

MODELLING TRANSITION RISK-ADJUSTED PROBABILITY OF DEFAULT

by Manuel Cugliari*, Alessandra Iannamorelli* and Federica Vassalli*

Abstract

This paper introduces a novel methodology to estimate the effect of climate-related transition risk on the one-year probability of default of Italian non-financial firms. To this end, we derive a granular dataset integrating the EU Emissions Trading System (EU-ETS) with market and corporate financial data. Within the EU-ETS framework, firms with emissions above (below) their free allocated allowances generate additional costs (revenues), which can potentially affect their creditworthiness. We then run stochastic simulations on the price volatility of EU-ETS futures and an extreme event risk analysis on their distribution to generate price scenarios. We assess the extent to which the costs of (revenues from) excess (negative) emissions affect firms' financial statements under different price scenarios. Our findings suggest that this approach provides a more precise assessment of the impact of transition risk on firms' creditworthiness than the one based on the scenarios of the Network for Greening the Financial System, for a few firms, the rating is upgraded. Furthermore, our framework aligns the transition risk horizon with the standard twelve-month timeframe in credit risk assessment and allows for regular updates of credit ratings.

JEL Classification: G33, H81, Q50.

Keywords: credit risk, probability of default, climate-related transition risk, non-financial firms.

Sintesi

Il lavoro adotta una metodologia innovativa per stimare l'impatto del rischio di transizione climatica sulla probabilità di default a un anno delle imprese non finanziarie italiane. A tal fine, viene prima sviluppato un dataset che combina informazioni relative al Sistema di scambio di quote di emissione dell'UE (EU-ETS) con dati di mercato e finanziari aziendali; nell'EU-ETS, a emissioni superiori (inferiori) alle quote assegnate corrispondono costi (ricavi) aggiuntivi per le imprese, con un possibile impatto, pertanto, sul relativo merito creditizio. Utilizzando simulazioni stocastiche sulla volatilità dei prezzi *futures* EU-ETS e analisi di rischio di eventi estremi sulla loro distribuzione si generano scenari su cui viene valutato l'effetto del costo (ricavo) delle emissioni in eccesso (difetto) sul bilancio aziendale. I risultati suggeriscono che l'analisi presentata nel lavoro permette di valutare l'impatto del rischio di transizione sul merito di credito delle imprese in maniera più accurata rispetto al metodo basato sugli scenari del Network for Greening the Financial System; per alcune imprese si osserva anche un miglioramento del merito di credito. Inoltre, il metodo adottato nel lavoro allinea l'orizzonte del rischio di transizione al periodo di dodici mesi tipico della valutazione del merito di credito e consente aggiornamenti tempestivi di quest'ultimo.

---

* Bank of Italy, Financial Risk Management Department.

CONTENTS

1. Introduction[1]

Embedding climate-related transition risk[2] into the credit risk assessment for non-financial firms has gained significant importance within the climate policy agenda, reflecting regulators' increasing commitment. In 2021, the European Central Bank (ECB) outlined a strategic plan to incorporate climate-related risk within its regulatory frameworks (European Central Bank, 2021). Within their mandate, central banks also need to manage climate change risk to protect their balance sheets from related financial risks (Boneva *et al.*, 2021). In this context, the Eurosystem has developed minimum standards to account for transition and physical risks in the ratings produced by In-House Credit Assessment Systems (ICASs) (Auria *et al.*, 2021).[3] ICASs rate banks' credit claims granted to non-financial firms and eligible as collateral in monetary policy operations. At the end of 2021, ICASs accounted for 34 per cent of the value of non-marketable collateral after haircuts. They play an important role in ensuring the quality and quantity of such collateral, protecting the Eurosystem's balance sheet and supporting a smooth monetary policy implementation.

Applying differentiated haircuts to collateral based on their climate risk profile, can incentivize the transition to a low-carbon economy, while still maintaining 'market neutrality' (McConnell *et al.*, 2022). However, the scarcity of precise and consistent data on risk exposures at the individual firm level undermines accuracy in the transition risk assessment. There is a need for more granular data to effectively evaluate firm-specific risks in the context of climate change (Financial Stability Board, 2021).

We propose to employ a unique granular dataset on verified emissions from the European Union Emissions Trading System (EU-ETS) to estimate the effect of carbon-price related transition risk on the one-year probability of default (PD) of Italian non-financial firms. We rely on market-based stochastic simulations of carbon price trajectories and fundamental-based stress tests of PDs to measure individual transition risk regarding emission costs. Departing from Grundmann *et al.*, (2023), we use conditional Value at Risk (CVaR) as a measure to select a risk-tailored extreme scenario across simulations. Then, we project the shocked carbon price impacts on a firm's PD by revaluating its financial statement. This research contributes to the ongoing initiatives in Banca d'Italia, aiming at expanding the credit risk assessment according to the ECB minimum standards for Eurosystem internal source for rating credit claims.

Firm emissions are a key production component and their cost is a critical element for quantify the firm PDs. The EU-ETS market provides direct insights into individual firm emissions, allowing for a more accurate bottom-up transition risk assessment than the standard top-down approach. This contrasts with the standard top-down method, which approximates firms' emissions based on sectoral data using employee count as a proxy (Faiella *et al.*, 2022). Thus, our paper addresses the shortcomings of the top-down approach, showing the relevance of accurate emission data for quantifying credit risk under adverse carbon price scenarios. The EU-ETS is the largest carbon market in the world for trading emission allowances, covering around 40 per cent of the EU greenhouse gas (GHG) emissions (DG Clima, 2023). The EU-ETS futures market is highly liquid for emissions trading (Kanzig, 2023) and its price variations are affected by existing and prospective climate policies (Dhamija *et al.*, 2017). Such dynamics allow the use of EU-ETS price data to construct multiple scenarios of EU-ETS possible allowances price trajectories through stochastic simulations. Our stress-test methodology employs both a baseline and an extreme scenario derived through tail analysis (Ordonez,

[1] We are grateful to Paolo Parlamento for his valuable contributions in the analysis of the firm balance sheet from the perspective of climate risk and to anonymous referee for useful comments. The views expressed in the paper are those of the authors and do not necessarily reflect those of the Bank of Italy.

[2] In the broader context of climate change risk, transition risk refers to investment losses from economic activities affected by climate policies.

[3] For further details on ECB minimum standard see Kording and Resch, 2022.

2022). Namely, we use a CVaR criterion to select a risk-tailored extreme scenario, explicitly targeting the average most unfavourable 5 per cent of outcomes in our simulated price trajectories.

The scenario analysis extends beyond the traditional 'asymmetrical' stress test approach of firm balance sheets, which typically focuses only on additional costs due to high emissions. In contrast, the proposed framework also considers the potential for firms to generate revenue from allowances. A firm that emits less than its allocated quota can sell its excess allowances on the market, generating additional revenues. This approach recognises the proactive measures that firms can take to reduce emissions and benefit financially from such actions. We rely on the Banca d'Italia ICAS (BI-ICAS) to estimate the transition risk-adjusted PDs (Giovannelli et al., 2020). Our main finding is that the PDs generated through EU-ETS-based scenario analyses demonstrate greater sensitivity to transition risk than the ones generated through Network for Greening the Financial System (NGFS) scenarios,[4] allowing for a more realistic estimate of rating migrations, encompassing both downgrades and upgrades. In our framework, price trajectories can be easily aligned with the typical one-year horizon of standard credit risk assessments, solving the existing horizon mismatch with the longer timeframes of the NGFS.

Our approach to incorporating transition risk into credit risk assessment diverges from traditional frameworks. Firstly, we design a bottom-up approach to calculate direct emissions precisely (Scope 1), using verified emissions data from the EU-ETS scheme. Our method differs significantly from top-down approaches. It also differs from those bottom-up approaches that either rely on estimated data from external providers or on data reported according to the Non-Financial Reporting Directive (NFRD), which may suffer from data quality issues (Grundmann *et al.*, 2023). Secondly, for future EU-ETS certificate prices, we develop multiple scenarios using stochastic simulations and select two statistically risk-tailored price scenarios. This contrasts with traditional approaches relying on a predefined NGFS scenario in addition to the baseline one. Thirdly, we apply the above methodology both to listed and not-listed firms, thanks to a fundamental-based projection of transition costs into firm balance sheets. This contrasts with the market-based approaches like carbon premium estimation, which limit the scope to listed firms. Lastly, we synchronise the timeframe of our scenario simulations with the BI-ICAS horizon, ensuring alignment and relevance for the standard credit risk assessment.

The remainder of this paper is organized as follows: Section 2 presents a literature review; Section 3 describes the emission data collection and compares the proposed bottom-up approach with a standard top-down approach; Section 4 and 5 present, respectively, the empirical methodology and the results. Section 6 performs a robustness exercise, while Section 7 concludes.

2. Literature review

The EU-ETS market

Market-based environmental policy tools are classified into quantity-based mechanisms like 'cap and trade' and price-based mechanisms, like carbon taxes (Stavins, 2003). The EU-ETS belongs to the 'cap and trade' class, implying that a maximum limit for GHG emissions produced by participating firms' installations is set

[4] The NGFS is a group of central banks and regulatory authorities established in 2017 after the Paris Agreement to enhance international cooperation to reach the target of keeping the maximum temperature rise below 2°C with respect to the pre-industrial levels The NGFS Climate Scenarios explore the impacts of climate change and climate policy to provide a common reference framework. The Orderly and Disorderly scenarios explore a transition consistent with limiting global warming to below 2°C. The Hothouse world scenario leads to severe physical risks.

at the European Economic Area level. Participating firms can buy or sell quotas as needed. One European Emission Allowance (EUA) equals 1 ton of CO2 (or an equivalent amount of another GHG). Every year, participating firms must return allowances for each ton of CO2 equivalent (tCO2eq.) emitted. A limited number of emission quotas is assigned free of charge to selected firms based on harmonised rules. Firms not provided with free allowances, or exceeding their free allocations, must buy allowances either at auctions or from firms having them in excess. Non-compliance leads to sanctions.

In contrast with a carbon tax system, where the price is fixed per 'unit of pollution' while the quantity is free to vary, in a carbon market like EU-ETS, the total quantity of emissions is fixed, and the price is free to vary based on the demand for certificates. Therefore, the price of the certificates can be high during an economic expansion and low during a recession (Taschini, 2023). The EU-ETS market flexibility compared to price-based mechanisms lies in the quota allocation, in the trading systems, and in the predetermined quota reduction, aiding firms in planning and selecting cost-effective energy compositions and long-term investments to reduce emissions (Bustamante and Zucchi, 2022).[5] Within the European Union legislation, Italy adopted the EU-ETS as the main measures for the reduction of greenhouse gas emissions. Thus, Italian firms belonging to the sectors with the greatest impact on climate change are expected to manage their emissions through EU-ETS.

The EU-ETS supply cap was set to decrease at a predetermined rate in each of the four phases of the system (Phase I-IV).[6] However, other factors affect the supply side, including the opportunity to save or borrow certificates over time, as well as a plan for global integration. On the other side, demand for certificates mainly arises from three categories of entities: energy producer firms, energy consumer firms (i.e. belonging to other industrial sectors), and financial firms or investment funds. Demand-side price drivers include borrowing, auctioning (Chevallier, 2012) and energy prices (Krokida *et al.*, 2020 and Gargallo *et al.*, 2021), the transition from fossil fuels to renewable sources, as well as extreme weather conditions (Alberola *et al.*, 2008, Christianen *et al.*, 2005; Mansanet-Bataller *et al.*, 2007).

---

[5] In low-emission years, member states can save unused allowances for subsequent years and in high-emission years borrow a limited amount of emissions from subsequent years (European Commission, 2023).

[6] The first two phases (Phase I and II, 2005-2012) involved national emission limits (National Allocation Plans - NAPs) with free allocations for most polluting sectors. Phase III (2013-2020) transitioned to a single emission limit at the European level, with free allocations based on a sectoral benchmark. Phase IV (2021-2030) introduced a decreasing European emission limit recalibrated against the benchmark, aiming at a 62 per cent reduction in GHG emissions by 2030 compared to 2005.

Figure 1 - EU Carbon Price measured by the spot price of EUA contracts traded on the EEX market.

Source: Bloomberg.

For these reasons, the EU-ETS market price dynamics have been heterogeneous across phases (see Figure 1). The initial decentralised emission limitation system led to an aggregated CO2 volume limit higher than the actual emissions, reducing prices. In Phase III, the introduction of stringent limits and an auction system was expected to lead to an increase in prices of allowances. However, the sovereign debt crises had a significant impact on overall productive activities, leading to a decrease in economic output and, consequently, in carbon prices. The low surplus in emissions and low carbon prices discourage green technology investment, thus hindering the goal of a 'cap-and-trade' system in mitigating and contrasting climate change. In 2019, the European Commission established the Market Stability Reserve (MSR)[7] to address the surplus of allowances. MSR purpose is to improve the system resilience to major shocks by adjusting the supply of allowances to be auctioned. In March 2023, the MSR was extended until 2030 to protect the EU from CO2 price drops due to external shocks like COVID-19. Several studies recognise that environmental policy announcements affected price formation during Phases I and II of the EU-ETS market (Fan *et al.*, 2017; Guo *et al.*, 2018; Yu *et al.*, 2022). In Phase IV, stricter CO2 and trade limits helped further increase prices, especially with the adoption of more restrictive measures by the European Commission in July 2021 (European Commission, 2021).

EUA certificates are traded on both spot markets, such as the Blue Next in Paris, the European Energy Exchange (EEX) in Leipzig or the Nord Pool in Oslo, and futures markets, such as the EEX and the ICE in London, with the latter markets being particularly liquid (Rittler, 2012 and Stefan and Wellenreuther, 2020). The liquidity feature of futures EUA markets, lead a broad set of literature to model price volatility using GARCH models (Engle, 2002). Through VaR analysis, milestone works by Benz and Truck (2008) and Taschini and Paolella (2008) demonstrate the predictive capabilities of simple GARCH models with an asymmetric component. Further studies show the asymmetric behaviour of EU-ETS spot and derivative market (Arouri *et al.*, 2012; Brauneis, 2016; Byun, 2013; Daskalakis, 2009; Dutta, 2018). Following such initial studies, the analysis focused on observing EUA futures returns to identify the typical motivations for choosing

[7] EU Commission Climate Action: https://climate.ec.europa.eu/eu-action/eu-emissions-trading-system-eu-ets/market-stability-reserve_it#market-stability-reserve.

the GARCH model, such as non-constant volatility and volatility clustering and leverage effect facts' (Zivot, 2009 and Wang and Ghysels, 2015).

Figure 2 – EU Carbon Price measured by the price of EUA futures contracts traded on the EEX market.

Source: Bloomberg.

Climate-related credit risk

The participation in the EU-ETS may affect firms balance-sheet, thus it has been studied for listed firm during Phase I to III. Typically, this research focuses on the 'carbon premium' and involves classifying firm portfolios as 'dirty' or 'clean' based on the number of free carbon allowances received by the firm. Namely, 'dirty' portfolios are related to a significant number of free certificates,[8] and vice versa for 'clean' ones. Due to environmental policy uncertainty, in the initial EU-ETS phases, 'dirty' portfolios yielded higher returns than 'clean' ones, confirming the existence of a carbon premium (Oestreich and Tsiakas, 2015 and Wen *et al.*, 2020). However, in Phase III, policies became more explicit, and the carbon premium proved to be directly linked to the difference between verified emissions and free-allocated allowances. With rising certificate costs, firms with emissions exceeding free quotas experienced a drop in stock prices, while firms with excess free quotas experienced an increase in stock prices (Bolton *et al.*, 2023). In other words, investors tend to demand a premium to be compensated for CO2 emission risk exposure (Bolton and Kacperczyk, 2021).

Besides, literature has increasingly focused on the integration of transition risk into credit risk assessment, with more attention paid to transition risk over physical risk due to the unpredictability of extreme natural events (Bernardini *et al.*, 2021). After initial studies on transition risk transmission to the financial system (Faiella and Malvolti, 2020 and Monasterolo, 2020), the analysis has evolved towards Credit Default Swap (CDS) spreads. Namely, firms are classified into 'green' or 'brown' portfolios based on their emissions (Scope 1 and 2),[9] as quantified in quantile distributions. By calculating the difference between the median CDS

[8] Recall that during Phase I and II the most polluting sectors received the highest number of free certificates.
[9] The Task Force on Climate-Related Financial Disclosure (TCFD) defined a harmonised set of rules to classify emissions (*Greenhouse Gas Protocol*) in three categories: Scope 1, 2 and 3. Scope 1 includes direct emissions related to the production, and Scope 2 covers indirect emissions, such as those related to acquired energy. Scope 3 emissions are all those related to the supply chain.

premium of green and brown firms, a transition risk exposure factor (Carbon Risk - CR) is obtained. Several studies have found a positive correlation between transition risk and the term structure of CDS, suggesting a significant long-term impact of transition risk on credit risk (see Blasberg *et al.*, 2021; Zhang and Zhao, 2022; Zhang *et al.*, 2023 among others). Currently, the prevalent approach for long-term integration of transition risk into credit risk assessment relies on NGFS-based scenario analysis (NGFS, 2021). NGFS scenarios combine long-term transition policy paths with short-term macroeconomic projections, factoring in recent energy prices and consumption data. Banks and supervision authorities use stress test exercises to assess the impact of the green transition on non-financial firms' and households' creditworthiness, incorporating energy dynamics and sectoral interactions. Scenario analyses usually employ Integrated Assessment Models (IAMs) for both stress test development (European Central Bank, 2022; Emambakhsh et al., 2023) and general transition risk-adjusted credit risk assessments (Battiston *et al.*, 2023; Billio and Giacomelli, 2023). Ordonez (2022) employs stochastic simulations to create multiple scenarios, projecting macroeconomic indicators and firm asset values in log returns. This risk-metric analysis performs tail risk assessments, including Value-at-Risk (VaR) and Expected Shortfall (ES), to analyse the impact of low-probability, high-impact events on portfolios.

Other authors apply carbon tax shocks to energy prices consistent with NGFS scenarios. For instance, Faiella *et al.*, (2022) assess the effects of different carbon taxes on credit quality of Italian firms taking into account energy demand elasticity to price. The analysis employs a top-down approach for deducing energy demand and emissions, proportionally allocating sectoral emissions to firms based on Eurostat data and employee numbers. Aiello and Angelico (2023) implement a similar methodology to evaluate the vulnerability of Italian banks to transition risk. This risk originates from the exposure of borrower firms to the transition risk factors. The authors' microsimulation model detects sector-specific impacts, correlating firm financial vulnerability with carbon taxation. The most considerable impact is on agriculture and services due to their less elastic energy demand. Di Virgilio *et al.*, (2024) further develop this approach, using sectoral attribution to estimate emissions for BI-ICAS evaluated firms. The NGFS scenarios projections on firms' balance sheets showed different effects on production costs, liquidity, income statements, and balance sheets, varying impacts across sectors. Such a top-down approach, while useful, has inherent limitations in precisely estimating individual emission levels and PDs. In response to ECB recommendations, some central banks are investigating using EU-ETS market data for an accurate assessment of firm-specific emissions. Such choice addresses the inaccuracies of the top-down approach by enabling precise calculation of emission levels and costs without relying on a generic carbon tax assumption. Grundmann *et al.*, (2023) detail the Bundesbank's approach of using a bottom-up method with EU-ETS data to integrate climate risk into the German ICAS. Despite a modest percentage of firms evaluated by the German ICAS are participants in the EU-ETS (2.76 per cent), their contribution to the total volume of firm emissions in Germany is notably significant (35.13 per cent). The proposed method considers two scenarios: one related to the current average EUA price and an extreme scenario aligned with the NGFS *Below 2°C* scenario. The extra cost of emission certificates is calculated as the difference between the average historical price for EUA certificates and the price for the following year, multiplied by the number of needed EUA certificates beyond free allocation. The extra cost is passed through both the income statement and the balance sheet to recalculate PDs. The results show little change in corporate riskiness under the current scenario, but a significant increase in the number of firms that may suffer a one or two-level rating downgrade in the extreme scenario.[10]

Our analysis represents a novel contribution, offering a more accurate perspective on credit rating changes in response to climate-related financial data. We describe that the existing literature predominantly focuses on listed firms, assessing the impact of transition risk on creditworthiness by calculating a risk premium - a 'carbon premium' - linked to their emissions (Blasberg *et al*., 2021 among others). Our methodology instead applies to both listed and unlisted firms since the transition risk impact on PDs is derived from the balance sheet stress

[10] Regarding the rating scale, we refer to the ICAS risk classes.

rather than from the market risk premium. Last, we align transition risk-adjusted PDs to typical credit risk one-year horizon, facilitating regular updates of credit ratings. To the best of our knowledge, this study is the first to evaluate transition risk using EU-ETS data for the credit assessment of listed and unlisted non-financial firms through stochastic simulations.

3. Data

3.1 Data sources

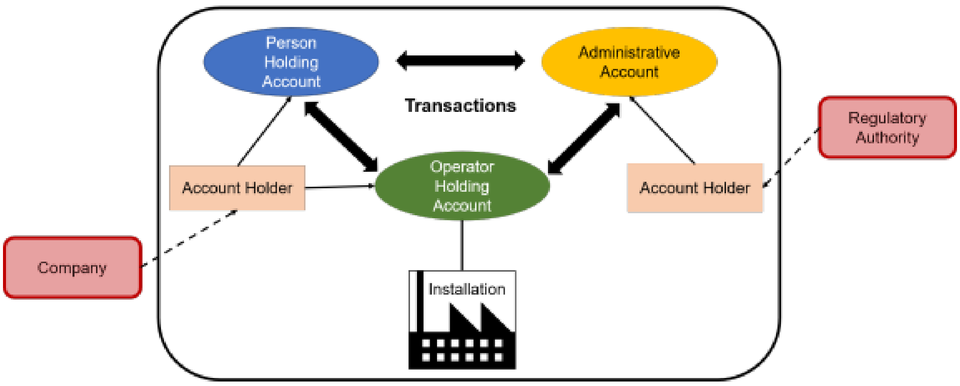
This study relies on three data sources: *i)* EU-ETS firm-level data[11] merged into an ad-hoc created dataset, *ii)* historical prices and volumes for both spot and futures allowance prices sourced from Bloomberg and *iii)* detailed information on firms' financial fundamentals, obtained from the BI-ICAS database described below.

EU-ETS data

According to the EU-ETS rules, every year, each registered entity has to submit to a climate-competent national authority a quantity of emission certificates at least equivalent to its verified emissions for the previous year. The National Registry of Emissions and Removals (RNER) collects the submitted certificates. The RNER, established under the European Commission Decision No. 389/2013/EU, is the authorities' monitoring instrument for all activities linked to emission allowances, including their initial allocation to firms and subsequent transactions up to cancellation. For Italy, the national authority is the Institute for Environmental Protection and Research (ISPRA). As RNER's managing bodies, national authorities like ISPRA ensure data transparency, security, and integrity. This role encompasses validating CO2 emissions produced by Italian corporations and supervising their compliance with European and domestic regulations.

As an open system, the EU-ETS allows regulated and unregulated members, including firms and individuals, to transact emission permits. An essential system component is the electronic registry, the European Union Transaction Log (EUTL), which facilitates and records the transfer of all participant certificates. As a central element of the EU ETS's settlement infrastructure, the EUTL involves several stakeholders, from corporate entities and their intermediaries to regulatory bodies and market operators, each with a dedicated account. Figure 3 below describes the structure of the EUTL registry.

Figure 3 - Entities operating within the EU-ETS system.



[11] EU-ETS data include verified emissions levels, firm compliance levels, and allocation of free allowances.

Source: Letout, 2022.

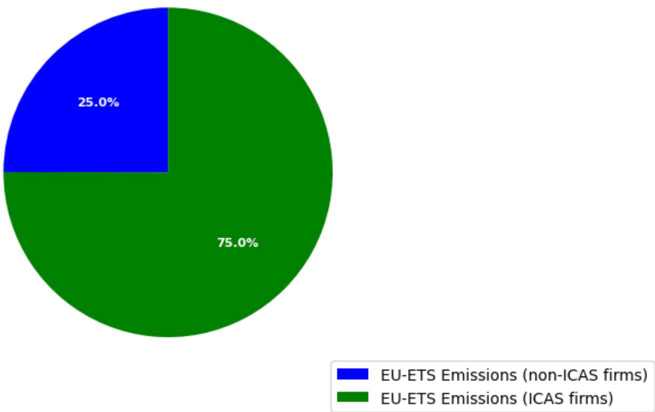
In the EU-ETS framework, installations represent the regulated entities. The responsibility for submitting emission certificates and the associated recording are managed at the installation level. Certificate transfers, or transactions, are conducted at the account level, with each installation linked to an 'Operator Holding Account' (OHA) managed by its operator. Regulatory authorities operate through 'Administrative Accounts' (AA) for allocating and receiving permits. Non-regulated participants, like intermediaries, use 'Person Holding Accounts' (PHA). The EUTL records each account's primary contact and tracks transactions between holders, allocating firms and regulatory authorities into the registry through their respective account holders to facilitate inter-system connections. From the EUTL records, we collected data on free allocated quotas and traded quotas at the firm level. Since each EUA quota represents 1 tCO2eq, we can calculate the total emissions for each firm (refer to Table 1). In 2022, 37 per cent of Italy's national emissions were traded as EUA quotas in the EU-ETS markets. A group of 542 ICAS firms (roughly 0.05 per cent of Italian non-financial firms), for which we have mapped transactions in EUA certificates, accounted for 75 per cent of the EU-ETS traded emissions, representing 28 per cent of Italy's total GHG emissions.

Table 1 - Contribution to national emissions in 2022 by Italian EU-ETS firms and BI-ICAS firms.

Emissions	tCO2eq.	per cent	N of firms	per cent
National emissions (ISPRA)	369.000.000	/	1.021.618	/
EU- ETS emissions	138.272.559	37	1200	0,12
ICAS emissions	103.738.358	28	542	0,05

Source: ISPRA, EUTL and BI-ICAS dataset.

Figure 4 – Contribution of BI-ICAS firms' emissions to the total Italian EU-ETS emissions.



Source: EUTL and BI-ICAS dataset.

Market data

The second pillar of the data needed for this study relates to the dynamics of EUA certificate trading, explicitly focusing on price trends and volume metrics as recorded in the EEX. Namely, from 2018 to 2023, we derive a historical series of both spot and futures prices of EUA certificates from Bloomberg. This choice provides a significant temporal perspective on EUA certificate prices, essential for understanding long-term trends and patterns within the EU-ETS. To ensure a comprehensive understanding of market movements, we opted for a daily frequency data collection, capturing the day-to-day fluctuations in the trading activity of EUA certificates.

Firms' financial data

The BI-ICAS database is the third data source used in this study. It includes both financial statement s data and credit behaviour data. Financial statements data are derived from the financial statements archive (Sistema Informativo Economico-Finanziario, SIEF) of Banca d'Italia, which incorporates data from the Cebi (Centrale dei Bilanci) and Cerved datasets. The Cebi dataset covers a significant portion of medium and large Italian firms and a limited portion of small firms; Cerved provides a more extensive dataset, covering almost all small and micro limited-liability firms (Giovannelli *et al*., 2020). We derive credit behaviour data from the National Credit Register (NCR) managed by Banca d'Italia. The NCR is a comprehensive archive of information on debtors' relationships with the banking financial system, updated monthly through reports contributed by banks and financial entities. We obtain the final dataset by merging the firm information in the BI-ICAS database with emission and transaction information included in the EU-ETS.

The above-described information is publicly accessible. However, in order to merge the EU-ETS database with the BI-ICAS for our study, structured relationships are needed. The merge is costly since no database that hierarchically represents the relationships among EU-ETS entities is available. Starting from the publicly available data from the European Commission, Abbrell (2022) develops a relational database for European installations, integrating various components of the EUTL registry to analyse firms' compliance with EU-ETS requirements and market behaviours. Letout (2022) further expands this work by linking the EU-ETS account holders to the Bureau van Dijk database,[12] achieving extensive coverage and high accuracy in identifying firms. Using the described methods, we create a new dataset by merging EUTL data with the BI-ICAS database, effectively combining the two sources. The fundamental element for implementing the merging process, which enables the association of installations with the specific BI-ICAS firms, is the information on Italian plants, available within a non-public database managed by ISPRA.[13] Using a specialised algorithm combining different matching techniques (detailed in Appendix A), we reconstruct emissions data for 572 BI-ICAS-listed companies. From now on, we will refer to these entities as the 'BI-ICAS sample'. Table 1 and Figure 3 report the coverage of the BI-ICAS sample for the year 2022.

3.2 Bottom-up vs top-down approach

To measure the gain in accuracy obtained by using a bottom-up approach rather than a top-down approach, we compare verified firm-reported emissions in the EUTL registry from the previous year with sector-attributed emissions for the BI-ICAS sample.[14] The traditional method of estimating emissions by matching sector-based Physical Energy Flow Account (PEFA)[15] data with data on firms' employee numbers provides a broad sectoral emission perspective, but lacks in precision at the firm level. With its detailed records of traded certificate volumes, the EU-ETS market provides a more accurate representation of each firm emissions and a clearer understanding of emission costs. The comparison, focusing on ICAS-registered companies in the EU-ETS,

---

[12] Bureau van Dijk is a Moody ' s Analytics Company that aggregates personal and financial information, ratings, shareholders, shareholdings and MandA on companies, banks and insurance companies from all over the world.

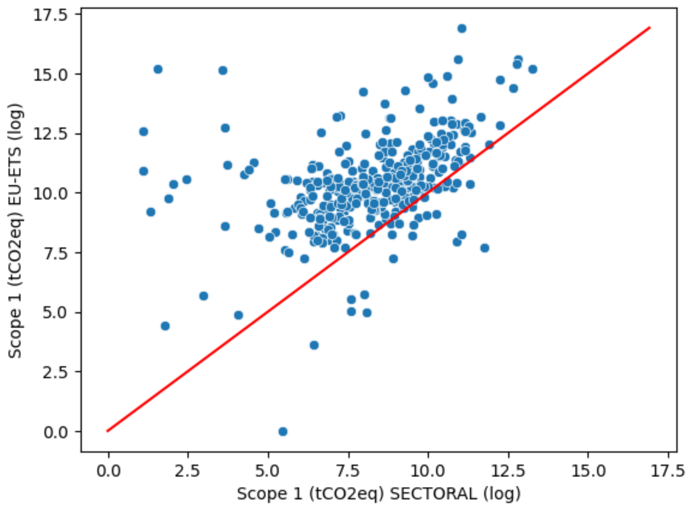
[13] Within its mandate to ensure monetary and financial stability, Banca d'Italia can access information on installation-level commitment with the EU-ETS requirements, like annual reports produced by the firm's installation managers and detailed assessments of plant energy consumption.

[14] To carry out the comparison the following data sources have been used: *i)* Eurostat for sectoral consumption and employees; *ii)* National Social Security Institute (INPS) for the number of company employees.

[15] PEFA, available in Eurostat, is an accounting statistical system that measures and quantifies energy flow within an economy – including its production, transformation, and consumption. This system provides crucial data for environmental and economic analyses, offering insights into energy utilisation and its impacts on various sectors.

highlights the need to refine and broaden the traditional approach, proposing an alternative way to quantify corporate emissions.

Figure 5 - EU-ETS verified firms' emissions versus sectoral imputation-based emissions.



Source: EUTL and Eurostat Scope 1 emissions.

Figure 5 represents a logarithmic scale scatter plot comparing EUTL granular data for firms assessed by BI-ICAS with the corresponding sectoral estimation of Scope 1 CO2 emissions (tCO2eq). The plot shows that sectoral attribution underestimates emissions, as most data points lie above the 45° line. Notably, the average difference between the emissions reported by EU-ETS firms and sectoral imputation-based emissions is 246,000 tCO2eq. The positive Spearman correlation of 0.51 indicates a significant monotonic relationship between sectoral and EU-ETS datasets. This suggests that, despite biases in magnitude, sectoral emissions estimates tend to follow the same general trend as EU-ETS-reported emissions. The discrepancy can be partly explained by the scope of the EU-ETS, which focuses on certified emissions from carbon-intensive activities, such as electricity and heat generation, energy-intensive industries, aviation, and maritime transport. Only high emitters participate in the EU-ETS, leaving smaller emitters out of its coverage. By contrast, sectoral imputation, relies on average estimates calibrated according to individual firm number of employees, which do not capture the variability in emissions among firms of the same size. The reliance on average values limits accuracy of sectoral attribution, especially for extreme emitters (Unnewehr *et al*., 2022).

4. Empirical methodology

4.1 A model for EU-ETS price dynamic

We treat CO2 emissions as a production input to estimate the additional costs implied by firm excess emissions based on the certificate prices. We focus on the futures market for EU-ETS allowances due to its liquidity and informative content (Stefan and Wellenreuther, 2020), in particular about future price expectations (Gorenflo, 2013). In Section 2, we conduct an in-depth analysis of the primary factors influencing the prices within the EU-ETS. Our focus is specifically on the timeframe from 2018 to 2023, which covers the transition from Phase III to Phase IV. During these phases, the European Commission clearly defined the policy measures, minimizing the likelihood of unexpected shifts in climate policy as the system's structure is predetermined and known to all stakeholders. We develop alternative price scenarios, which can be regularly updated, by modelling the volatility of futures prices and using stochastic simulations. Thus, this approach enables us to account for periods of high or low prices, which may arise from speculative bubbles, energy, or policy-related shocks.

The *first estimation step* involves modelling price volatility of *futures contracts* on EUA certificate. To this aim, we use GARCH models for estimating the variance of EUA futures certificate returns.[16] GARCH models (Engle, 2002) are widely used to capture the volatility dynamics of the financial markets. Namely, they effectively model some features of returns time series like conditional heteroscedasticity, non-normal return distributions, heavy tails (kurtosis), and left skewness. GARCH is also suited to modelling dynamic heteroscedasticity ('volatility clustering'), a feature of financial series where periods of high or low volatility persist over time. Additionally, they can capture the negative correlation between volatility and returns or 'leverage effect' (Black, 1976).

We perform a 'stylised facts' analysis (Zivot, 2009 and Wang and Ghysels, 2015), to show that the above features of financial returns also hold true for futures contracts on EUA certificates, justifying the choice of GARCH to model their volatility. Among GARCH models, we opt for an asymmetric parametric model in the form of GJR-GARCH (*p*, *K q*) (Glosten, 1993), allowing for a leverage effect. Leverage effect means that negative returns have a greater influence on future volatility than do positive returns. In fact, we observe that there is a negative correlation between volatility and past returns. Further details on model selection are provided in Appendix B. The general GARCH specification is the following:

$$r_t = \mu_t + \varepsilon_t \tag{1}$$

$$\mu_t = E(r_t | F_{t-1}) \tag{2}$$

$$\sigma_t^2 = Var(r_t | F_{t-1}) \tag{3}$$

Where r_t is the daily return, μ_t is the expected value of returns, ε_t is a generic shock to the conditional volatility σ_t^2 at time t, F_{t-1} is the information set at time $t-1$. In the GJR-GARCH, σ_t^2 evolves according to the following equation:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{k=1}^{K} \gamma_k I_{t-k} \varepsilon_{t-k}^2 + \sum_{j=1}^{q} \beta \sigma_{t-i}^2 \tag{4}$$

$$I_{t-i} = \begin{cases} 0 \text{ if } r_{t-i} \geq \mu \\ 1 \text{ if } r_{t-i} < \mu \end{cases} \tag{5}$$

Where $\omega > 0, \alpha_i \geq 0, \beta_j \geq 0$ are bounded parameters representing a sufficient condition to ensure a positive variance. The shock ε_t can be written as $\varepsilon_t = \sigma_t z_t$, with z_t quantile from the Normal distribution. The indicator function in Equation 5 is typical of GJR-GARCH specification. It assigns a coefficient γ_i to below-average returns to account for the leverage effect. Parameters p and q are the lags for the shocks and for the autoregressive conditional volatility, respectively; K is the number of asymmetric parameters. Using the Bayesian optimization procedure (Naik *et al.*, 2020), the model is set with $p = 2, q = 2, K = 1$. This setup allows modelling conditional volatility for $T + h$ periods ahead through Monte-Carlo simulations of the ε_{t-i}^2 shock. In our case h amounts at 252 days, equivalent to one year. Using standard tests, such as the

[16] Log return are commonly defined as: $r_t = \log(P_t) - \log(P_{t-1})$, where r_t is the daily return of EUA certificates, obtained as log difference of closing prices of adjacent days (P_t and P_{t-1}). We model via GARCH the variance σ^2 of EUA certificate futures returns, linked to EUA certificate futures price volatility through the standard relationship: $\sigma^2 = Var(r_t)$.

Unconditional Coverage test (UC, Kupiec, 1995), the Conditional Coverage test (CC, Christoffersen, 1998), and the Dynamic Quantile test, we validate the VaR of GJR-GARCH model for variance (see Appendix B for further details). To construct the scenarios, we use the average variance for the baseline scenario and extract an extreme scenario by considering tail variances (Ordonez, 2022). By exploiting the volatility and the relation $r_t = \mu_t + \sigma_t z_t$, we get one-year ahead trajectories for EUA futures certificate price. Note that scenarios are not price forecasts, but descriptions of market trajectories.

The *second estimation step* consists in quantifying the extra production cost that firms have to bear for GHG emissions. Building upon Grundmann *et al*., (2023), we get the extra cost as follows:

$$EC_{i,t} = ExtraEUA_{i,t} \times (\hat{P}_{EU-ETS,t+1} - P_{EU-ETS,t}) \quad (6)$$

Where $ExtraEUA_{i,t}$ represents the EUA certificates exceeding the free allocated quotas for firm *i* traded in the current year, $\hat{P}_{EU-ETS,t+1}$ is the simulated unit price 12 month ahead estimated via the GJR-GARCH, while $P_{EU-ETS,t}$ is the volume weighted average price certificate over the last 12 months.[17] The additional cost of EU-ETS quotas can be positive or negative, depending on the firms surrendering quotas. Firms exceeding their free allocated certificate limits face a deficit and must buy certificates. Conversely, firms with emissions below their allocation have a surplus and can sell their excess quotas. Transition plans may improve carbon efficiency, supporting the surplus channel. However, since transition plans are typically designed for long-term implementation, their impact on the one-year timeframe of our analysis may be less significant compared to that of short-term certificate management policies.

Grundmann *et al*., (2023) explore both a current and a stressed scenario. In the current scenario, the price is set at the average EUA price in 2022, while in the extreme scenario, a price consistent with the NGFS' orderly transition' scenario is assumed. They compute the additional costs based on these prices and stress the balance sheet accordingly. In this study, we employ stochastic simulations to generate alternative price scenarios. We apply a CVaR approach, focusing on the average of the worst 5 per cent outcomes in the extra cost distribution calculated for the upcoming year based on the simulated price trajectories.

The proposed methodology offers a dual advantage. Firstly, precise estimation of firm emissions via EUA certificates enables a balanced assessment of firm creditworthiness, accounting for firm incurring costs to match their emissions with allowances and firms profiting from selling excess certificates. Secondly, it employs stochastically simulated price trajectories, helping align the transition risk estimation horizon with standard practices in credit risk assessment. This method is inherently sensitive to price fluctuations allowing for frequent updates of PD estimates. In addition to transition risk, it incorporates the market risk implicit in EU-ETS that participating firms have to face. Considering the extra cost, which adjusts the current year's cost against the previous one, the approach effectively accounts for the impacts of high or low price phases, including when depending on bubbles, energy and policy shocks.

4.2 The transmission of transition costs through firm balance sheet

Since 2013, BI-ICAS has been one of the sources for the assessment of collateral agreed upon within the Eurosystem Credit Assessment Framework (ECAF). It estimates the PDs of Italian non-financial firms and allows banks to pledge credit claims as collateral for monetary policy operations (Giovannelli *et al*., 2020). The BI-ICAS rating process involves a two-stage procedure, including a quantitative analysis based on a statistical model and a qualitative analysis based on an expert assessment. We focus on the statistical model to

[17] For each firm *i*, $ExtraEUA_{i,t}$ is calculated as the difference between EUA certificates exceeding the free allocated. See Section 3.1 on how we get free allocated and traded quotas at firm level.

stress-test financial statements with additional costs related to EUA certificates. Employing logistic regressions, the BI-ICAS statistical model generates a one-year PD by integrating credit behaviour data from the NCR and financial statement data. We rely on the reclassified financial statement indicators to examine how deficit or surplus scenarios in emission quotas affect the PD estimations. This assessment is reflected in the latest firm balance sheet (2022).

In the first scenario (firms in deficit), based on the accounting principles defined by the Organismo Italiano di Contabilità (OIC),[18] we assume that the firm adds the extra cost to the income statement following the need to buy extra quotas[19] to align realised emissions with the allowed ones ('+ C_{add}') in Table 2. The corresponding balance sheet item is cash outflow. Suppose cash and equivalents are not large enough to cover the cash outflow. In that case, we assume that the firm negotiates a new short-term debt, which implies an increase in interest expenses ('+ C_{int}').[20] The higher costs decrease operating margins and net income, negatively affecting equity. The deterioration of the balance sheet is partially offset by a reduction in taxation ('- E_{tax}')[21] resulting from a lower taxable income. Overall, the net effect on the financial component of the PD estimation is negative (see Tables 2 and 3).[22]

Table 2 – Transmission of extra-costs of emissions on Income Statement (firms in deficit).

Income Statement (Reclassified)	**Effect**
+ Net sales	
+ Other revenues	
- Cost of goods sold	
Gross Profit	
- Operating expenses	**+ C_{add}**
EBITDA	
- Amortisation and Depreciation	
EBIT	
+/- Net financial income	
- Interest expenses	+ C_{int}
EBT	
- Tax expenses	**- E_{tax}**
Net Income (Loss)	**-**

[18] OIC is an accounting Italian institution that consistently sets and updates national accounting principles with international standards.

[19] For the analysis, we do not consider the balance sheet effects of a hypothetical scenario where firms with surplus EUA certificates store them for future use. While this behaviour is typical in normal operations, we assume that a company would prefer to sell these certificates for short-term liquidity in case of financial distress. Therefore, we presume the immediate sale of excess certificates for the transition risk-adjusted PD calculation. Aligning with national accounting principles, it is worth noting that modelling a 'storage' scenario would not affect excess free certificates. However, for a surplus of previously purchased certificates, there would be a reduction in previously recorded costs, offset by a deferred income entry, maintaining cash flow effects and limiting PD variation.

[20] The cost of new debt is assumed equal to the estimated debt cost for the current year (Return on Debt 'ROD').

[21] The reduction in taxation is obtained as $E_{tax} = (C_{add} + C_{int}) \times t$, where t is the tax rate equal to 27,9%.

[22] The firm financial statements analysis also considers the 'net liability approach'. This approach involves recording free quotas as intangible assets at nominal (zero) value. Purchased quotas are recorded as fixed assets with an indefinite useful life and are not subject to depreciation. However, they are recognised in the income statement in the relevant period under miscellaneous operating expenses. Given the analysis assumptions, the methodology described and the one used can be considered equivalent.

Table 3 - Transmission of extra-costs of emissions on Balance Sheet (firms in deficit).

Balance Sheet (Assets)	**Effect**
Fixed Assets	
…	
Current Assets	
Cash and cash equivalents …	**- C_{add} - C_{int} + E_{tax}**
Total Assets	**-**
Balance Sheet (Liabilities and Equity)	**Effect**
… + / - Net Income (Loss)	**- C_{add} - C_{int} + E_{tax}**
Equity	
…	
Long-Term Debt	
…	
Short-Term Debt	
Short-term financial debt	**+ C_{add} + C_{int} - E_{tax}** (if cash is not enough)
Total Liabilities and Equity	**-**

In the second scenario (firm in surplus), we assume that the firm sells the extra quotas, generating a non-operating revenue ('+ R_{add}') with the subsequent increase in cash and equivalents. Selling quotas implies an improvement in the financial component of the PD estimation. The new revenue positively contributes to cash, margins and operating results, thus reducing leverage. In this case, we consider the fiscal effect consisting of higher taxation ('+ E_{tax}'),24 due to higher income (see Tables 4 and 5).

Table 4 - Transmission of extra-costs of emissions on Income Statement (firms in surplus).

Income Statement (Reclassified)	**Effect**
+ Net sales + Other revenues - Cost of goods sold	+ R_{add}
Gross profit	
- Operating expenses	
EBITDA	
- Amortisation and Depreciation	
EBIT	
+/- Net financial income - Interest expenses	
EBT	
- Tax expenses	+ E_{tax}
Net Income (Loss)	+

Table 5 - Transmission of extra-costs of emissions on Balance Sheet (firms in surplus).

Balance Sheet (Assets)	**Effect**
Fixed Assets	
…	
Current Assets	
Cash and cash equivalents …	+ R_{add} - E_{tax}
Total Assets	+
Balance Sheet (Liabilities and Equity)	**Effect**
… + / - Net Income (Loss)	+ R_{add} - E_{tax}
Equity	
…	
Long-Term Debt	
…	
Short-Term Debt	
Short-term financial debt	
Total Liabilities and Equity	+

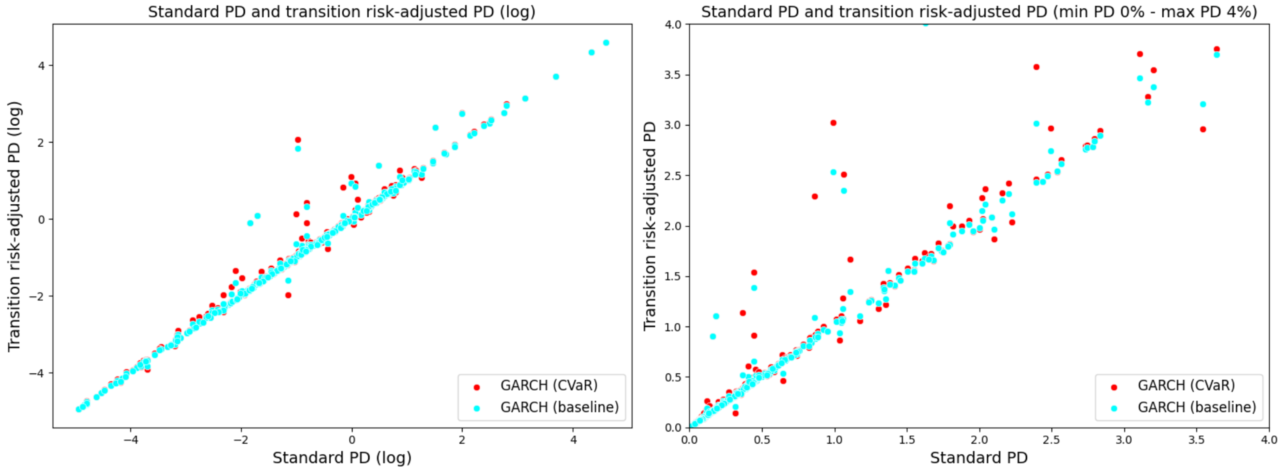
5. Results

5.1 Transition risk for Italian firms

The methodology applied in this study quantifies transition risk through the additional cost associated with GHG emissions in order to assess its impact on firm creditworthiness. Risk quantification leverages EU-ETS data to accurately determine emissions' volume and cost and their simulated multiple price trajectories. In order to project excess emission costs into firm financial statements, we select two scenarios: a baseline and an extreme one. The baseline scenario builds upon the average certificate price projected over a year through 10,000 GJR-GARCH model runs via Monte Carlo simulations. Based on such simulated price trajectories, the extreme scenario is defined by the CVaR approach, focusing on the average of the worst 5 per cent outcomes in the extra cost distribution.

Figure 6 shows a scatter plot comparing the transition risk-adjusted PDs obtained in the two scenarios (y-axis) against the standard ICAS PDs (x-axis). The plot features two panels: the left panel displays data for the entire sample on a logarithmic scale, while the right panel reports PD (truncating PD levels at a maximum value of 4 per cent). In the baseline scenario (cyan points), the probabilities are close to the 45° line, indicating a slight variation of transition risk-adjusted PDs from standard estimates. In contrast, the extreme scenario (scattered red points) shows more significant PD variability than the baseline scenario. Points above the 45° line represent firms with worsened PDs due to increased certificate prices and extra costs. Points below the line represent companies with improved PDs due to reduced emissions compared to their free certificate allocation, leading to extra revenues. The baseline scenario analysis found no significant PD changes, indicating that firms historically capable of absorbing carbon costs continue to do so. Only the abrupt shifts in carbon pricing affect firm creditworthiness, leading to notable changes in their PD levels.

Figure 6 – 1-year probability of default sensitivity to transition risk. Baseline scenario vs CVaR scenario.



Note: Cyan points represent the baseline scenario PDs, and red points represent the CVaR scenario PDs. The left panel reports PDs in the logarithm scale; in the right panel, PDs are in percentage.

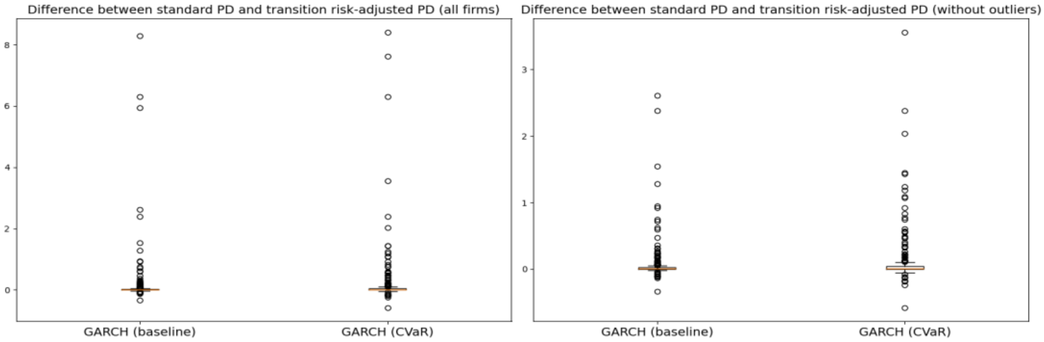
Table 6 provides a comparative analysis of credit rating migrations across two scenarios. As for credit rating, we rely on the BI-ICAS scale. The CVaR-based extreme scenario is more cautious, preserving the credit rating for only 83 per cent of firms, as opposed to 90 per cent in the baseline scenario. Notably, the extreme scenario leads to more downgrades (about 14 per cent of firms) and more upgrades in credit ratings compared to the baseline (3 per cent versus 1 per cent), in line with the distribution patterns observed in Figure 6. Migration dynamics provide supporting evidence for the sensitivity and effectiveness of the EU-ETS-based methodology. It demonstrates that transition risk affects firms through price shifts that have not yet been absorbed, both positively and negatively.

Table 6 - 1-year change in credit ratings for GJR-GARCH baseline and CVaR (per cent).

Method	**Stable**	**Upgrade**	**Downgrade**
GJR-GARCH (base)	90	1	9
GJR-GARCH (CVaR)	83	3	14

Figure 7 displays box-whisker plots illustrating the difference between transition risk-adjusted and standard PDs for both the extreme and the baseline scenarios. The left panel includes all data, while the right panel omits extreme values to focus on the central range of data. In line with the findings observed in Figure 6, Figure 7 shows that the baseline scenario has a tighter cluster of PD variations around zero. In contrast, the extreme scenario exhibits a more dispersed PD distribution, reflecting a wider range of variations in the PDs.

Figure 7 – 1-year probability of default variation under the baseline scenario and the extreme scenario.

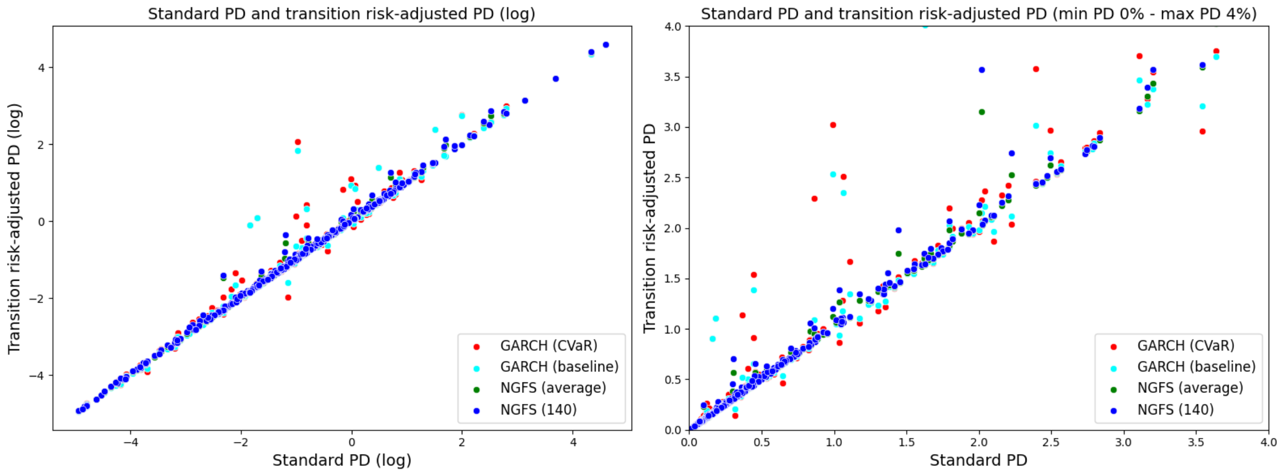


Note: The left panel presents all firms in the sample, while the right panel excludes outliers for clarity. The Y-axis displays the absolute difference between standard PDs and transition risk-adjusted PDs in percentage.

5.2 EU-ETS vs NGFS-based scenario analysis

The one-year horizon of our proposed methodology contrasts with the common practice of relying on long-term (8/10 years) NGFS scenarios (Emambakhsh *et al*., (2023) among others). Through BI-ICAS, we compare the sensitivity of firm PDs to the transition risk assessed via EU-ETS data against the transition risk assessed via NGFS scenarios. To perform the comparison, we firstly artificially shorten the NGFS scenarios to a one-year timeframe by front-loading the price impact on the first year, and we secondly associate to each NGFS scenario three possible carbon taxes: *Below 2°C* – 40€/tCO2eq., *Net Zero 2050* – 90€/tCO2eq and *Delayed Transition* – 140€/tCO2eq (Di Virgilio *et al*., 2023). The comparison resulted in differing responses of firm PDs to transition risk quantified by carbon market data or by a fixed carbon tax. The scatter plots reported in Figure 7 compare the transition risk-adjusted PDs obtained with the two alternative methodologies against the standard PDs of the BI-ICAS sample. The left panel shows the full range of insolvency probabilities on a logarithmic scale, while the right panel focuses on the most concentrated area. For comparability, in Figure 7, we plot only the baseline and the CVaR-based extreme scenarios with two NGFS scenarios, an average of the three and the worst case (*Delayed Transition* – 140€/tCO2eq). Compared to the 45° line, the placement of data points demonstrates that the baseline EU-ETS scenario (cyan points) exhibits more variability than the adverse NGFS scenario (blue points), with a broader dispersion around the line. The PDs for the average NGFS scenario (green points) and the adverse NGFS scenario (blue points) align more closely with the 45° line, indicating minimal deviation from standard PD estimates. The extreme EU-ETS scenario (red points) shows more significant variability, with data points widely scattered above and below the 45° line, suggesting significant fluctuations in transition risk-adjusted PDs.

Figure 8 - 1-year probability of default under the baseline ETS scenario, extreme CVaR ETS scenario, average NGFS scenario, and adverse NGFS scenario.



Note: Cyan points represent the baseline scenario PDs, and red points represent the CVaR scenario PDs under the EU-ETS methodology. Green points represent the average NGFS scenarios PDs, and the blue points represent the worst NGFS scenario (140€/tCO2eq. tax). The left panel reports PDs in the logarithm scale; in the right panel, PDs are in percentage.

To compare all the alternative methodologies in terms of credit rating movements, we rely on Table 7. The new methodology, both in baseline and CVaR scenarios, shows a more responsive approach in adjusting risk classes, especially in terms of improvements, compared to the carbon tax and sectoral data emission estimation approach (see Section 3.2). The NGFS scenarios, despite their varying carbon tax values, tend to keep around 90 per cent of firms in the same risk class, indicating a lower sensitivity to transition risk. The underestimation of emissions in sectoral approaches and the lack of a mechanism to reward environmentally responsible firms, like selling quotas in the EU-ETS market, lead to lower sensitivity. Additionally, NGFS scenarios focus only on policy-driven decarbonisation targets, based on pre-defined assumptions on their implementation. In contrast, the EU-ETS-based approach incorporates market dynamics, to which participating firms are inherently exposed beyond the effects of transition policies, including both general speculative movements and those specific to the EU-ETS. When carbon prices rise, firms selling certificates in the EU-ETS market gain additional revenue, enhancing their creditworthiness. In the baseline scenario, 1 per cent of firms benefit from trading EUA certificates, while 3 per cent improve their rating class in an extreme scenario. In addition, in the extreme EU-ETS scenario, when firms incur additional costs, we observe 14 per cent of firms being downgraded. This contrasts with a 12 per cent downgrade under the extreme NGFS scenario (Delayed Transition), highlighting the EU-ETS scenario's effectiveness in evaluating firms' financial risks related to emissions.

Table 7 - Migration of 1-year credit rating classes generated by the alternative methodologies (per cent).

Method	Stable	Upgrade	Downgrade
GJR-GARCH (CVaR)	83	3	14
GJR-GARCH (base)	90	1	9
Below 2°C (40 €/tCO2)	94	0	6
Net Zero 2050 (90 €/tCO2)	91	0	9
Delayed Transition (140 €/tCO2)	88	0	12
Average of NGFS scenarios	91	0	9

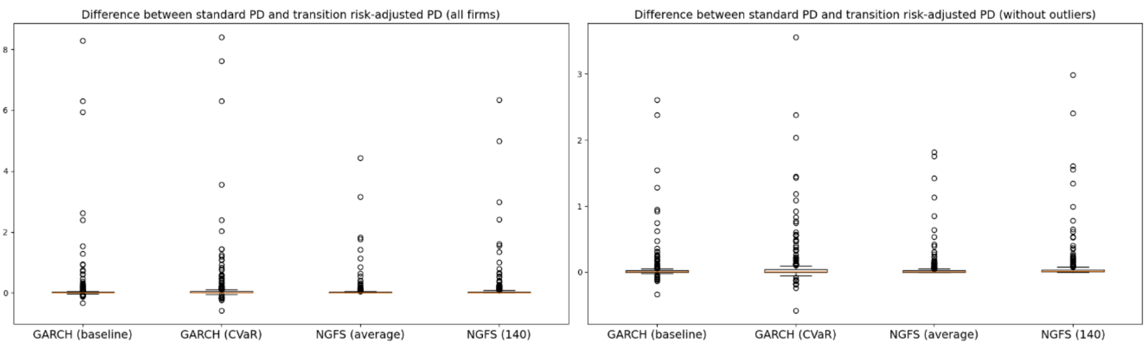
Finally, Table 8 shows some descriptive statistics to compare further the methodologies: average value of the differences between transition risk-adjusted PD and standard PD expressed in percentage, standard deviation, coefficient of variation (CV), and finally, the Gini Index. The table allows the ranking of the alternative methodologies based on the average difference in transition risk-adjusted PDs compared to the standard PD. The methodology proposed in this research is notably more responsive to transition risk quantified through carbon price shocks, as indicated by the higher sensitivity and lower concentration of the EU-ETS-based approach than the NGFS ones. The Gini Index and the CV scores under the stochastic method reflect less concentration due to specific rather than sectoral data.

Table 8 – Descriptive statistics about variations 1-year probability of default across alternative methodologies (per cent).

Method	Mean	Std. Dev.	CV	Gini Index
GJR-GARCH (CVaR)	0.06	0.22	3.65	10
Delayed Transition (140 €/tCO2)	0.05	0.13	2.75	78
GJR-GARCH (base)	0.04	0.15	4.21	11
Net Zero 2050 (90 €/tCO2)	0.03	0.08	2.70	78
Average of NGFS scenarios	0.03	0.08	2.68	78
Below 2°C (40 €/tCO2)	0.01	0.04	2.67	77

Despite the broader variability observed in the outcomes, the central tendencies, such as the mean adjusted PDs, remain broadly aligned with those derived from NGFS scenarios. This similarity in magnitude reflects a convergence of transition risk impacts at an aggregate level. However, the added granularity of our model provides insights into firm-level risks and their dispersion across sectors, capturing heterogeneity in transition risk profiles that sectoral averages may overlook. While NGFS scenarios utilize sectoral averages that compress the tails of the distribution, smoothing extreme variations, our approach captures real-world market fluctuations, including firm-specific emissions data. This results in a broader range of predicted PDs and a higher sensitivity to transition risks. Figure 10, which compares box plots of alternative methodologies, further supports the evidence of higher sensitivity, thus variability, of the proposed methodology to climate-related shocks. As we can appreciate in the left panel, the distribution of the EU-ETS-based approach is more scattered than the NGFS-based ones. This is true also when omitting the outliers (right panel).

Figure 9 – 1- year probability of default variation under alternative scenarios.



Note: The left panel presents all firms in the sample, while the right panel excludes outliers for clarity. The Y-axis displays the absolute difference between standard PDs and risk-adjusted PDs in percentage.

To further look into the two methodologies based on EU-ETS allowances price evolutions and NGFS scenarios, we compare the relevant PD distributions. The comparison involves all the firms in the BI-ICAS sample participating in the previously analysed EU-ETS scheme and a subset excluding firms with more free certificates than emissions (Table 9). The Kolmogorov-Smirnov and Mann-Whitney U tests confirmed different distributions for the two samples. The Spearman correlation coefficient (0.67) indicated some agreement in stress intensity between methodologies, decreasing to 0.41 when including firms with lowered default probabilities.

Table 9 – Tests on statistical distribution on 1-year probability of default under alternative methodologies.

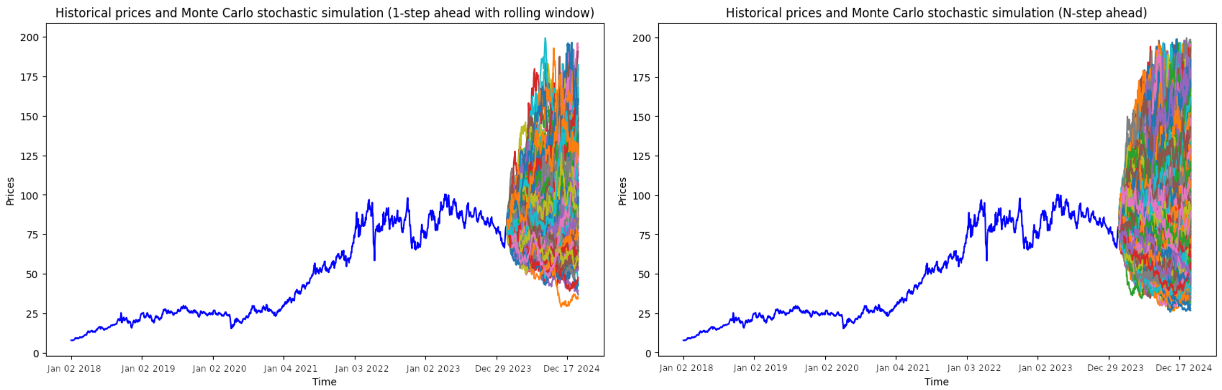
Method	Kolmorogov-Smirnov	Mann-Whitney U	Spearman
GJR-GARCH CVaR vs Average NGFS scenario (only firms experiencing costs)	0.00	0.00	43
GJR-GARCH CVaR vs Average NGFS scenario (including virtuous firms)	0.00	0.00	69

Note: p-values for Kolmorogov-Smirnov and Mann-Whitney U. Data for Spearman represents the percentage of correlation.

6. Consistency check

Our findings are robust and not dependent on the estimated conditional volatility of EUA *futures* prices. In the literature, asymmetric GARCH models, particularly the GJR-GARCH model, are preferred for modelling the volatility of EUA allowances during Phases III and IV. Our stochastic simulation method uses a Monte Carlo n-step ahead simulation for the error term, producing multiple return trajectories based on one-year average volatility. Using a 252-day rolling window, we forecast 1-step ahead volatility, leading to 10,000 one-year return paths and corresponding price trajectories. These trajectories, as observed in Figure 10, remain within a consistent range.

Figure 10 - Comparison of price simulated trajectories with 1-step ahead rolling window (left panel) and with N-step ahead (right panel)



Note: the left panel represents the historical price and the 10.000 estimated trajectories one year ahead with the 1-step ahead rolling window. The right panel represents the historical price and the 10.000 estimated trajectories one year ahead with the N-step.

As indicated in Table 10, there is no significant variation in credit rating migration resulting from the two techniques to project trajectories, affirming the robustness and reliability of our results.

Table 10 – Comparison in migration of credit rating classes (per cent).

Method	Stable	Upgrade	Downgrade
N-steps ahead			
GJR-GARCH (CVaR)	90	1	9
GJR-GARCH (base)	83	3	14
Rolling window			
GJR-GARCH (CVaR)	91	1	8
GJR-GARCH (base)	86	1	13

7. Conclusion

This paper aims to improve non-financial firms' credit risk assessment by incorporating transition risk into the estimate of a transition risk-adjusted PD. Our methodology employs EU-ETS market data, including prices and transaction details, to quantify transition risks accurately. To assess the impact of transition risk on firms' creditworthiness, we focus on the implications of carbon pricing on firms' financial statements. We rely firstly in employing a bottom-up methodology based on EU-ETS transactions to quantify GHG emissions of Italian non-financial firms. This method bridges the shortcomings of the top-down sectoral approach, which often underestimates emissions and their associated costs. Secondly, the proposed methodology considers the options where firms either incur extra costs from excess emissions or financially benefit by selling surplus quotas. This dual assessment allows for a more symmetrical evaluation of the financial impact of emissions-related initiatives on firms. We also depart from the standard NGFS scenario analysis by employing stochastic simulations to model EUA futures price trajectories. By applying the GJR-GARCH model to forecast volatility, we derive future price paths through Monte Carlo simulations. Simulated prices enable the quantification of extra costs for participating firms in the EU-ETS in both baseline and extreme scenarios. In the baseline scenario, extra costs are the difference between excess certificates over free allocation multiplied by the average of simulated prices and of the previous year's costs. A CVaR approach is applied for the extreme scenario, focusing on the worst 5 per cent price distribution cases. This methodology aligns the scenario simulation with the BI-ICAS's one-year horizon, typical in credit risk assessments.

Our findings indicate that such methodology is notably responsive to transition risk shocks, as reflected in PD variations. It effectively responds to cost and revenue changes, affecting ratings through downgrades or upgrades for environmentally responsible firms. Quantifying emissions through emission allowances enables environmentally responsible firms to benefit from transition risk, improving their ratings. To the best of our knowledge, this study is unique in combining a bottom-up approach with stochastic simulation of transition risk scenarios over a one-year horizon, diverging from the use of predetermined long-term NGFS scenarios. This paper demonstrates that EU-ETS market data enhance a more accurate and responsive transition risk assessment compared to top-down sectoral emissions estimations and NGFS scenarios. An accurate evaluation of transition risk could yield a dual impact. On the one hand, from the banking sector viewpoint, variations in PDs influence the valuation of the collateral eligible for monetary policy operations. On the other hand, from an enterprise's perspective, firms with higher emissions face more constraints in borrowing relative to low-emission ones (Altavilla *et al*., 2023).

Future expansions would include accounting for transition plans as a risk mitigation tool.[23] To verify the existence and credibility of a transition plan, we could rely on the Non-Financial Declaration (NFD), firms' balance sheets, and the database managed by SBTi, where declared transition plans are recorded and certified. The credibility of each plan can be verified by comparing each firm's announced emission reduction announced with the actual reduction, as inferred from the historical trend of traded quotas in the EU-ETS (Carbone *et al*., 2021).

Also, we consider exploring scenarios where environmentally virtuous firms save excess certificates for future use and where non-virtuous firms pass additional costs onto final prices, with the overall impact contingent on the price elasticity of their products.

[23] A climate transition plan is a detailed action plan that outlines how a firm will modify its business model to achieve net zero carbon emissions by 2050. Transition plans are essential for showing stakeholders that the firm is committed to reducing emissions and ensuring the business remains profitable in a net-zero carbon economy. Thus, we consider incorporating the transition plans' impact on carbon emissions into the calculation of the difference between produced emissions and allocated quotas, which should be annually reduced by the fixed established percentage (see Section 2).

References

Abbrell, J. (2022). *EU ETS info*. Retrieved from https://www.euets.info/

Aiello, A., and Angelico, C. (2023). Climate change and credit risk: The effect of carbon taxes on Italian banks' business loan default rates. *Journal of Policy Modeling, 45*(1), 187-201

Alberola, E., Chevallier, J., and Cheze, B. (2008). The EU emissions trading scheme: The effects of industrial. *International Economics, 116*, 93-125

Altavilla, C., Bouchina, M., Pagano, M., and Polo, A. (2023). Climate risk, bank lending, and monetary policy. *Centre for Studies in Economics and Finance, 687*

Arouri, M., Jawadi, F., and Khuong, D. (2012). Nonlinearities in carbon spot-futures price relationships during Phase II of the EU ETS. *Economic Modelling, 29*(3), 884-892

Auria, L., Bingmer, M., Mateo, C., Charavel, C., Gravilà, S., Iannamorelli, A., Levy, A., Maldonado, A., Resch, F., Rossi, A. M., and Sauer, S. (2021). Overview of central banks' in-house credit assessment systems in the euro area. *ECB Occasional Paper, 284*

Battiston, S., Mandel, A., Monasterolo, I., and Roncoroni, A. (2023). Climate credit risk and corporate valuation. *Available at SSRN 4124002*

Benz, E., and Truck, S. (2008). Modeling the price dynamics of CO2 emission allowances. *Energy Economics, 31*(1), 4-15

Berkowitz, J., Christoffersen, P., and Pelletier, D. (2011). Evaluating value-at-risk models with desk-level data. *Management Science, 57*(12), 2213-2227

Bernardini, E., Faiella, I., Lavecchia, L., Mistretta, A., and Natoli, F. (2021). Central banks, climate risks, and sustainable finance. *Questioni di Economia e Finanza, 608*

Billio, M., and Giacomelli, A. (2023). ESG-adjusted credit rating: The indirect approach

Black, F. (1976). Studies of stock market volatility changes. *Proceedings of the American Statistics Association, Business and Economic Statistics Section, 1976*

Blasberg, A., Kiesel, R., and Taschini, L. (2021). Climate default swap: Disentangling the exposure to transition risk through CDS. Available at *SSRN*

Bolton, P., and Kacperczyk, M. (2021). Do investors care about carbon risk? *Journal of Financial Economics*, *142*(2), 517-549

Bolton, P., Lam, A., and Muuls, M. (2023). Do carbon prices affect stock prices? *Available at SSRN*

Boneva, L., Ferrucci, G., and Mongelli, F. P. (2021). To be or not to be ‘green’: How can monetary policy react to climate change? *ECB Occasional Paper Series, 285*, 1-40

Brauneis, A. Z. (2016). Modeling carbon spot and futures price returns with GARCH and Markov switching GARCH models. *Central European Journal of Operations Research, 24*, 149-176

Bustamante, M. C., and Zucchi, F. (2022). Dynamic carbon emission management. *ECB Working Paper, 2885*

Byun, S. J. (2013). Forecasting carbon futures volatility using GARCH models with energy volatilities. *Energy Economics, 40,* 207-221

Carbone, S., Giuzio, M., Kapadia, S., Kramer, J., Nyholm, K., and Vozian, K. (2021). The low-carbon transition, climate commitments, and firm credit risk. *ECB Working Paper, 2631,* 70

Chevallier, J. (2012). *Econometric analysis of carbon markets.* London: Springer

Christianen, A., Arvanitakis, A., Tangen, K., and Hasselknippe, H. (2005). Price determinants in the EU emissions trading scheme. *Climate Policy, 1*(5), 15-30

Christoffersen, P. (1998). Evaluation of interval forecasts. *International Economic Review, 18*(2), 111-128

Daskalakis, G. D. (2009). Modeling CO2 emission allowance prices and derivatives: Evidence from the European trading scheme. *Journal of Banking and Finance, 33*(7), 1230-1241

DG Clima. (2023). Participation in the EU ETS markets. *Europe Economics*

Dhamija, A., Surendra, S., and Jain, P. (2017). Forecasting volatility of carbon under EU ETS: A multi-phase study. *Environmental Economics and Policy Studies, 19,* 299-335

Di Virgilio, S., Faiella, I., Mistretta, A., and Narizzano, S. (2024). Assessing credit risk sensitivity to climate and energy shocks. Towards a common minimum standards in line with the ECB climate agenda. *Journal of Policy Modeling, 46*(3), 552-568

Dutta, A. (2018). Modeling and forecasting the volatility of carbon emission market: The role of outliers, time-varying jumps, and oil price risk. *Journal of Cleaner Production, 172,* 2773-2781

Emambakhsh, T., Fuchs, M., Kordel, S., Kouratzoglou, C., Lelli, C., Pizzighello, R., and Spaggiari, M. (2023). The road to Paris: Stress testing the transition towards a net-zero economy. *ECB Occasional Paper, 328*

Engle, R. (2002). New frontiers for ARCH models. *Journal of Applied Econometrics, 17*(5), 425-446

Engle, R., and Manganelli, S. (2004). CAViaR: Conditional autoregressive value at risk by regression quantiles. *Journal of Business and Economic Statistics, 22*(4), 367-381

European Central Bank. (2021). ECB presents action plan to include climate change considerations in its monetary policy strategy. Retrieved from https://www.ecb.europa.eu/press/pr/date/2021/html/ecb.pr210708_1~f104919225.en.html

European Central Bank. (2022). ECB takes further steps to incorporate climate change into its monetary policy operations. Retrieved from https://www.ecb.europa.eu/press/pr/date/2022/html/ecb.pr220704~4f48a72462.en.html

European Commission. (2021). *Fit for 55: Delivering the EU's 2030 Climate Target on the way to.* Retrieved from https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52021DC0550

European Commission. (2023). *Our ambition for 2030.* Retrieved from https://climate.ec.europa.eu/eu-action/eu-emissions-trading-system-eu-ets/our-ambition-2030_en?prefLang=it

Faiella, I., and Malvolti, D. (2020). The climate risk for finance in Italy. *Questioni di Economia e Finanza, 545*

Faiella, I., Mistretta, A., and Lavecchia, L. (2022). A climate stress test on the financial vulnerability of Italian households and firms. *Journal of Policy Modeling, 44*(2), 396-417

Fan, Y., Jia, J. J., Wang, X., & Xu, J. H. (2017). What policy adjustments in the EU ETS truly affected the carbon prices?. *Energy Policy, 103,* 145-164.

Financial Stability Board. (2021). *The availability of data with which to monitor and assess climate-related risks to financial stability*

Gargallo, P., Lample, L., Miguel, J., and Salvad, M. (2021). Co-movements between EU ETS and the energy markets: A VAR-DCC-GARCH approach. *Mathematics, 9*(15), 1787

Giovannelli, F., Iannamorelli, A., Levy, A., and Orlandi, M. (2020). The in-house credit assessment system of Banca d'Italia. *Questioni di Economia e Finanza, 586*

Glosten, L. R. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *The Journal of Finance, 48*(5), 1779-1801

Gorenflo, M. (2013). Futures price dynamics of CO2 emission allowances. *Empirical Economics, 45,* 1025-1047

Grundmann, J., Silberbach, A., and Auria, L. (2023). Including carbon taxation risk in Deutsche Bundesbank's in-house credit assessment system (ICAS): An empirical analysis. *Deutsche Bundesbank Technical Paper*

Guo, J., Su, B., Yang, G., Feng, L., Liu, Y., and Gu, F. (2018). How do verified emissions announcements affect the comoves between trading behaviors and carbon prices? Evidence from EU ETS. *Sustainability, 10*(9), 3255

Kanzig, D. (2023). The unequal economic consequences of carbon pricing. *NBER Working Paper Series*, 1-44

Kording, J., and Resch, F. (2022). Common minimum standards for incorporating climate change risks into in-house credit assessment systems in the Eurosystem. *ECB Economic Bulletin, 6*/2022

Krokida, S.-I., Lambertides, N., Savva, C., and Tsouknidis, D. (2020). The effects of oil price shocks on the prices of EU emission trading system and European stock returns. *The European Journal of Finance, 26*(1), 1-13

Kupiec, P. H. (1995). Techniques for verifying the accuracy of risk measurement models. *The Journal of Derivatives, 95*(24)

Letout, S. (2022). Corporate micro-data in the EU Emission Trading System (EU ETS). *Publications Office of the European Union*

Mansanet-Bataller, M., Pardo, A., and Valor, E. (2007). CO2 prices, energy, and weather. *Energy, 28*(3-5), 73-93

McConnell, A., Yanovski, B., and Lessmann, K. (2022). Central bank collateral as a green monetary policy instrument. *Climate Policy, 22*(3), 339-355

Monasterolo, I. (2020). Climate change and the financial system. *Annual Review of Resource Economics, 12*, 299-320

Naik, N., Mohan, B. R., and Jha, R. A. (2020). GARCH-model identification based on performance of information criteria. *Procedia Computer Science, 171*, 1935-1942

NGFS. (2021). NGFS: Climate scenarios for central banks and supervisors

Oestreich, A., and Tsiakas, I. (2015). Carbon emissions and stock returns: Evidence from the EU emissions trading scheme. *Journal of Banking and Finance, 58*, 294-308

Ordonez, G. (2022). Moody's integrated risk analysis. *Moody's Analytics*

Rittler, D. (2012). Price discovery and volatility spillovers in the European Union emissions trading scheme: A high-frequency analysis. *Journal of Banking and Finance, 36*(3), 774-785

Stavins, R. N. (2003). Experience with market-based environmental policy instruments. *Handbook of Environmental Economics, 1*, 355-435

Stefan, M., and Wellenreuther, C. (2020). London vs. Leipzig: Price discovery of carbon futures during Phase III of the ETS. *Economics Letters, 188,* 108990

Taschini, L. (2023). Carbon pricing and carbon markets. *LSE Executive Education*

Taschini, L., and Paolella, M. S. (2008). An econometric analysis of emission allowance prices. *Journal of Banking and Finance, 32*(10), 2022-2032

Unnewehr, J. F., Weidlich, A., Gfüllner, L., and Schäfer, M. (2022). Open-data based carbon emission intensity signals for electricity generation in European countries – Top-down vs. bottom-up approach. *Cleaner Energy Systems, 3,* 100018

Wang, F., and Ghysels, E. (2015). Econometric analysis of volatility component models. *Econometric Theory*

Yu, H., Wang, H., and Liang, Z. L. (2022). Carbon market volatility analysis based on structural breaks: Evidence from EU-ETS and China. *Experimental Science, 10*, 973855

Zhang, Y., Liu, Y., and Wang, H. (2023). How credit default swap market measures carbon risk. *Environmental Science and Pollution Research*

Zhang, Z., and Zhao, R. (2022). Carbon emission and credit default swaps. *Finance Research Letters, 50*, 103286

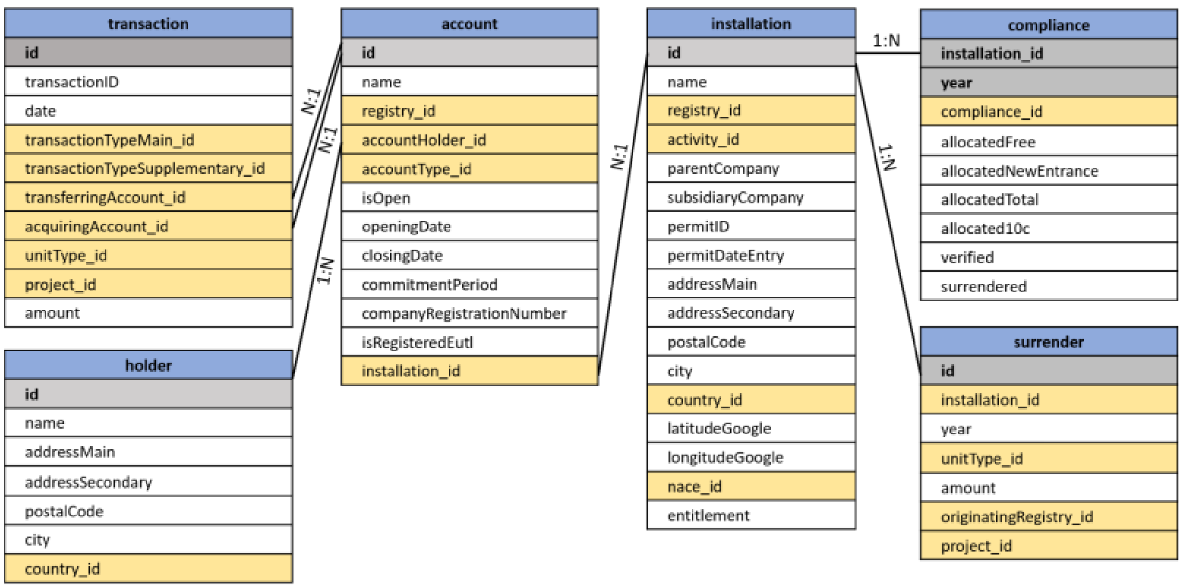
Zivot, E. (2009). Practical issues in the analysis of univariate GARCH models. *Handbook of Financial Time Series.* Berlin, Heidelberg: Springer Berlin Heidelberg

APPENDIX A

The diagram in Figure 11 illustrates the interconnectedness within the primary structures of the EUTL database. On the right side, every installation relates to multiple records in the compliance and surrender sectors. For each installation under the EU-ETS, the compliance dimension focuses on distributing and submitting permits alongside annually confirmed emissions. When it comes to surrendering, each installation corresponds to a specific entry in the surrender log, which is distinguished by the type and provenance of the surrendered item. At any given moment, a single operator's holding account is uniquely connected to an Installation. However, this representation of an Installation by an OHA can shift over periods.

Consequently, an installation may have connections to numerous OHAs. Post the 2012-13 overhaul of the EUTL, most installations are linked to a past operator's holding account (type 120-0) and a current one (type 100-7), leading to at least two linked accounts for most. Every account is directly associated with a solitary account holder, who may have links to multiple accounts. This connection helps in identifying accounts that are collectively owned. For instance, a prominent electricity firm operating several power stations would register multiple OHAs, one for each facility, often under a single account holder. Such a firm could also be linked to a PHA managing its trade through a centralised account. EUETS.INFO facilitates the exploration of these patterns by enabling searches of accounts via account holders and identifying related accounts based on the same holders.

Figure 11 - EUTL database relational model (Abbrell, 2022).



Transactions are defined by two accounts, identified as the donor and recipient of allowances. Each account partakes in numerous transactions, serving in both capacities. OHAs annually engage in at least two transactions, acquiring allowances to match their verified emissions. To comply with EU-ETS regulations, OHAs must then surrender these units, thus participating in a transaction as a donor. The algorithm developed for establishing connections initially uses the Legal Entity Identifier (LEI) or tax code as identifiers for the firms. In its final stage, the algorithm employs approximate matching techniques (fuzzy logic) between the demographic data of OHAs and specific identifying details of BI-ICAS firms (standardised names, postal codes, and geolocation information). This algorithm generates a likelihood score between the EUTL and BI-ICAS entries. This score allows the ranking of the combinations of data acquired: valid matches realise when the score for each of the three identifying details of the company exceeds a certain threshold. Table 11 displays the number of BI-ICAS enterprises included within the EU-ETS, distinguishing them based on the various matching techniques.

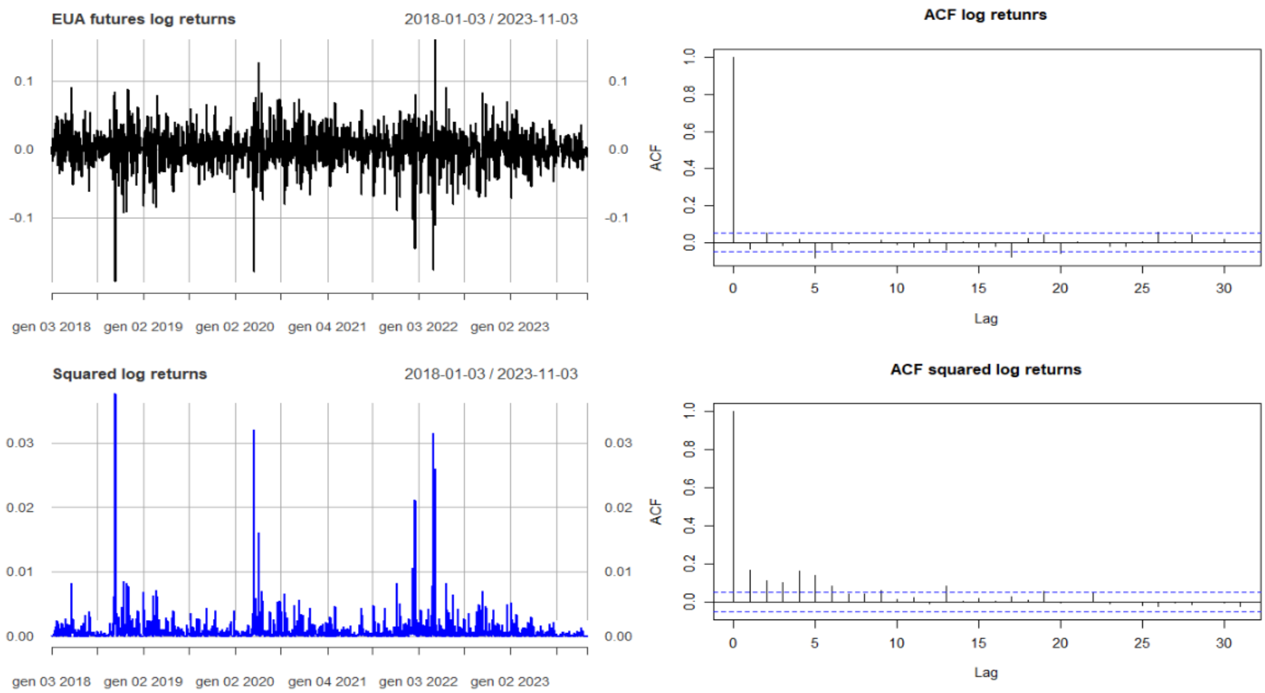
Table 11 - ICAS enterprises within EU-ETS grouped by correspondence criteria.

BI-ICAS firms within EU-ETS	**572**
Legal entity identifier	342
Tax code	61
Fuzzy logic	169

APPENDIX B

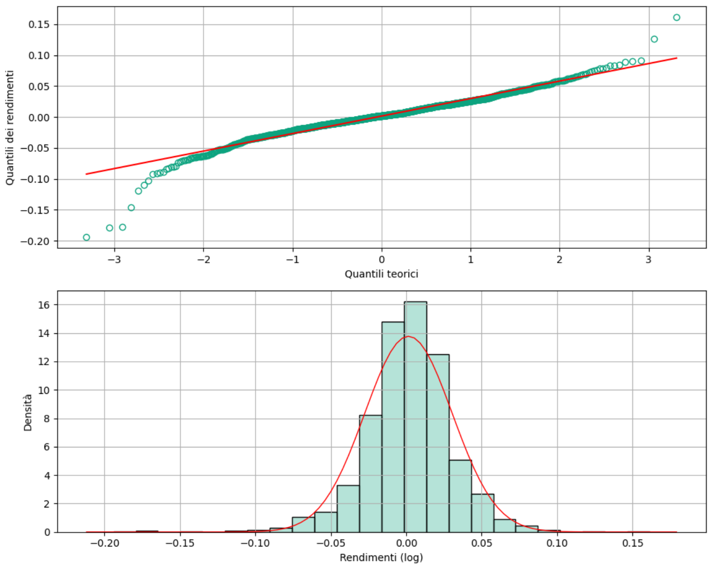
The features of EUA certificate futures returns are analysed through the examination of 'stylized facts' (Zivot, 2009 and Wang and Ghysels, 2015). The analysis, covering data from 2018 to 2023, reveals characteristics like non-constant volatility (conditional heteroscedasticity) and, less prominently, volatility clustering. This phenomenon is more apparent in the squared returns series. The autocorrelation function (ACF) chart indicates no autocorrelation, consistent with the series' nature, but shows correlation in squared returns. These findings suggest modelling the variance (second moment) of the futures price distribution rather than the series trend (see Figure 12).

Figure 12 - Time series of log returns (top left-side panel), squared log returns (bottom left-side panel). ACF for log returns and squared log returns (right-side panels).



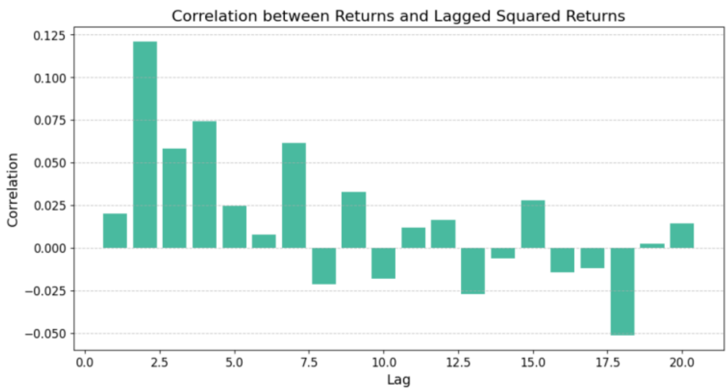
To analyse the distribution of EU-ETS returns, Figure 13 presents a Quantile-Quantile (QQ) plot and an estimation of data density compared to a normal distribution. Both panels reveal deviations from the normal in the tails. Specifically, the data distribution shows heavy tails (kurtosis = 7.89) and a leftward skew (skewness index = -0.6).

Figure 13 - QQ plot (top panel) and returns distribution (bottom panel).



The graphical inspection of the correlation between volatility and past returns, and the scatter plot between the two, reveals a negative correlation. This finding confirms the presence of a significant leverage effect, although it's less pronounced in the second analysis.

Figure 14 - Correlation between returns and volatility up to 20 lags (top panel). Returns vs volatility (bottom panel).



Our next step involves testing various GARCH specifications to identify the most suitable model for capturing the volatility of EUA certificates. We start with the simplest specification and progress to the more complex GARCH-MIDAS, which incorporates the monthly price of crude oil as a lower frequency variable. Initially, we assess model performance using the Akaike Information Criterion (AIC), as shown in Table 13, selecting the model with the lowest AIC value. Subsequently, we conduct a back-test analysis on VaR at 5 per cent confidence (Taschini and Paolella, 2008). This process involves comparing expected versus actual VaR violations (as detailed in the AE column of Table 12) and testing the statistical properties of the VaR. We utilize several tests for this purpose: the Unconditional Coverage test (UC, Kupiec, 1995), the Conditional Coverage test (CC, Christoffersen, 1998), and the Dynamic Quantile test (DQ, Engle and Manganelli, 2004). These tests evaluate whether the rate of VaR violations aligns with expectations and whether these violations are independently distributed over time. Notably, the DQ test, which also assesses the independence of VaR violations and the accuracy of violation counts (similar to the CC test), has been shown to be more powerful (Berkowitz *et al.*, 2011). Based on the results in Table 13, we have chosen the GJR-GARCH(2,1,2) model, with optimal parameters determined through Bayesian optimization (Naik *et al.*, 2020). Figure 15 illustrates the 5 per cent VaR estimation against EUA returns, demonstrating the model's ability to closely mirroring the series. For the sake of exposition, we report in Figure 16 all the estimated models.

Table 13 - Statistical properties of GARCH models.

	AIC	AE	UC	CC	DQ
GARCH-N	-4.37	85	0.19	0.41	0.7
GARCH-t	-4.42	91	0.41	0.56	0.2
GARCH skew-t	-4.42	85	0.19	0.37	0.1
EGARCH-N	-4.37	89	0.34	0.64	0.7
EGARCH-t	-4.42	95	0.64	0.84	0.2
GJR-N	-4.37	87	0.23	0.48	0.6
GJR-t	-4.41	92	0.48	0.59	0.2
GJR-t 22	-4.41	92	0.48	0.77	0.5
GARCH-MIDAS	-6.56	89	0.34	0.64	0.4
GARCH-MIDAS-t	-8.33	92	0.48	0.77	0.3
DAGM	-6.56	89	0.34	0.64	1.6
DAGM-t	-8.32	92	0.47	0.77	0.3

Note: data for the AIC column represent the value of the test, data for AE are in percentage, the others represent the p-value.

Figure 15 - VaR at 5 per cent level estimated with the selected GJR-GARCH.

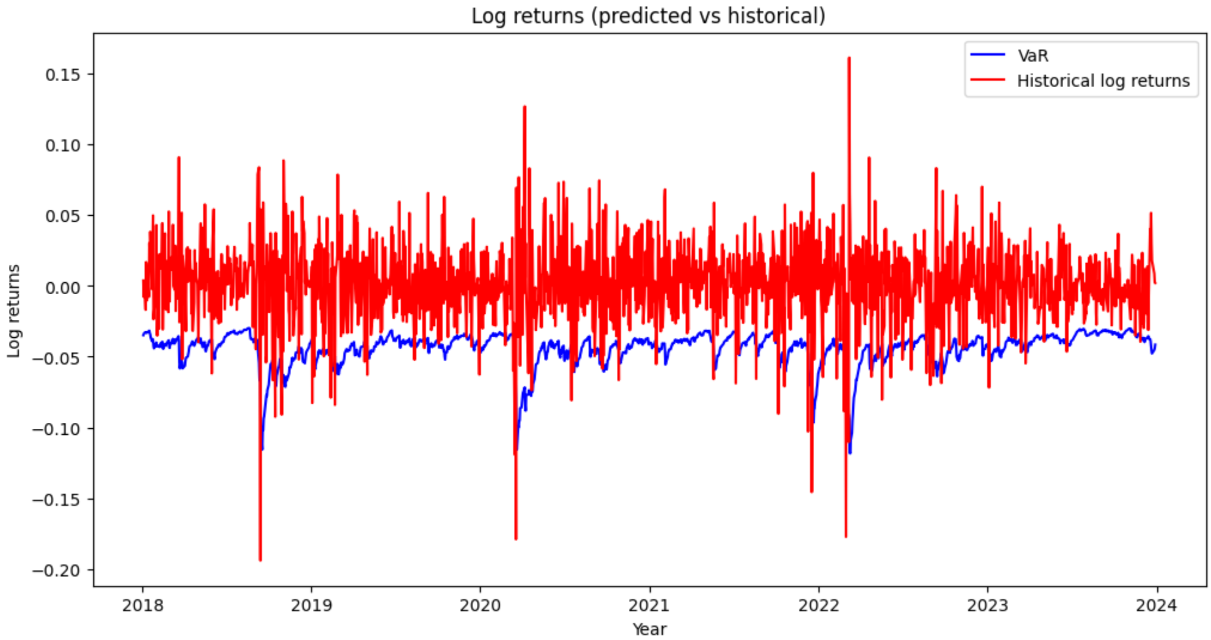
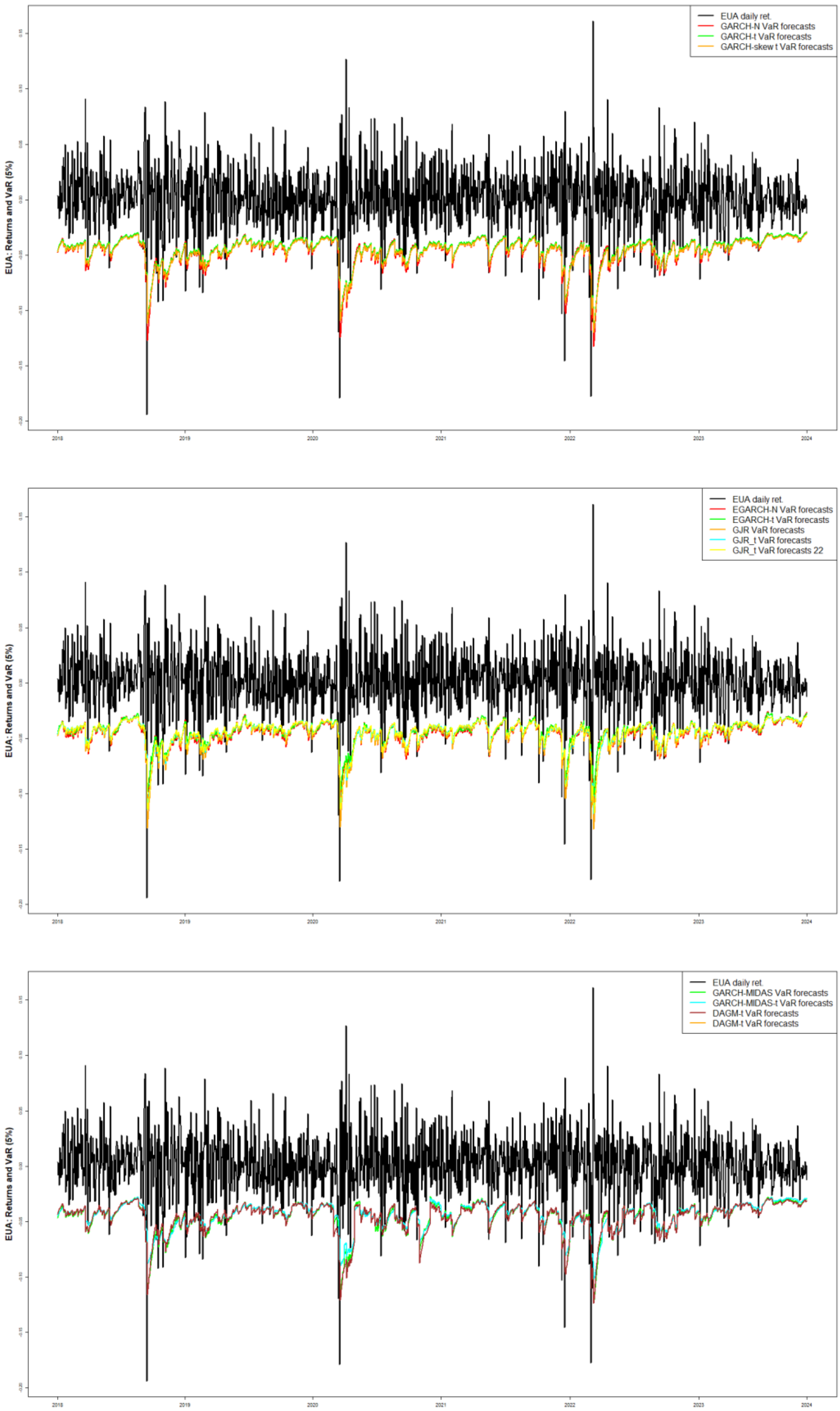


Figure 16 - Estimated VaR with simple model (upper panel), advanced model (medium panel) and MIDAS model (lower panel)



Recently published papers in the 'Markets, Infrastructures, Payment Systems' series

n. 22 When financial innovation and sustainable finance meet: Sustainability-Linked Bonds, *by Paola Antilici, Gianluca Mosconi and Luigi Russo* (Institutional Issues) (in Italian)

n. 23 Business models and pricing strategies in the market for ATM withdrawals, *by Guerino Ardizzi and Massimiliano Cologgi* (Research Papers)

n. 24 Press news and social media in credit risk assessment: the experience of Banca d'Italia's In-house Credit Assessment System, *by Giulio Gariano and Gianluca Viggiano* (Research Papers)

n. 25 The bonfire of banknotes, *by Michele Manna* (Research Papers)

n. 26 Integrating DLTs with market infrastructures: analysis and proof-of-concept for secure DvP between TIPS and DLT platforms, *by Rosario La Rocca, Riccardo Mancini, Marco Benedetti, Matteo Caruso, Stefano Cossu, Giuseppe Galano, Simone Mancini, Gabriele Marcelli, Piero Martella, Matteo Nardelli and Ciro Oliviero* (Research Papers)

n. 27 Statistical and forecasting use of electronic payment transactions: collaboration between Bank of Italy and Istat, *by* Guerino Ardizzi and Alessandra Righi (Institutional Issues) (in Italian)

n. 28 TIPS: a zero-downtime platform powered *by* automation, by *Gianluca Caricato, Marco Capotosto, Silvio Orsini and Pietro Tiberi* (Research Papers)

n. 29 TARGET2 analytical tools for regulatory compliance, *by Marc Glowka, Alexander Müller, Livia Polo Friz, Sara Testi, Massimo Valentini and Stefano Vespucci* (Institutional Issues)

n. 30 The security of retail payment instruments: evidence from supervisory data, *by Massimiliano Cologgi* (Research Papers)

n. 31 Open Banking in the payment system: infrastructural evolution, innovation and security, supervisory and oversight practices, *by Roberto Pellitteri, Ravenio Parrini, Carlo Cafarotti and Benedetto Andrea De Vendictis* (Institutional Issues) (in Italian)

n. 32 Banks' liquidity transformation rate: determinants and impact on lending, *by Raffaele Lenzi, Stefano Nobili, Filippo Perazzoli and Rosario Romeo* (Research Papers)

n. 33 Investor behavior under market stress: evidence from the Italian sovereign bond market, *by Onofrio Panzarino* (Research Papers)

n. 34 Siamese neural networks for detecting banknote printing defects, *by Katia Boria, Andrea Luciani, Sabina Marchetti and Marco Viticoli* (Research Papers) (in Italian)

n. 35 Quantum safe payment systems, *by Elena Bucciol and Pietro Tiberi*

n. 36 Investigating the determinants of corporate bond credit spreads in the euro area, *by Simone Letta and Pasquale Mirante*

n. 37 Smart Derivative Contracts in DatalogMTL, *by Andrea Colombo, Luigi Bellomarini, Stefano Ceri and Eleonora Laurenza*

n. 38 Making it through the (crypto) winter: facts, figures and policy issues, *by Guerino Ardizzi, Marco Bevilacqua, Emanuela Cerrato and Alberto Di Iorio*

n. 39 The Emissions Trading System of the European Union (EU ETS), *by Mauro Bufano, Fabio Capasso, Johnny Di Giampaolo and Nicola Pellegrini* (in Italian)

n. 40 Banknote migration and the estimation of circulation in euro area countries: the italian case, *by Claudio Doria, Gianluca Maddaloni, Giuseppina Marocchi, Ferdinando Sasso, Luca Serrai and Simonetta Zappa* (in Italian)