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TESIS DOCTORAL

Supervised learning in the improvement of public investment policies for the promotion of economic development.

El aprendizaje supervisado en la mejora de las políticas públicas de inversión para el fomento del desarrollo económico.

D. Diego Rodríguez-Linares Rey

2024

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Autor: D. Diego Rodríguez-Linares Rey

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ENVIRONMENTAL POLICY AND CARBON MARKETS: HOW EU-ETS VOLATILITY AFFECTS CORPORATE PERFORMANCE IN HIGH AND LOW EMISSION COMPANIES

SUMMARY IN SPANISH (RESUMEN EN ESPAÑOL)

Esta tesis doctoral presenta un estudio detallado del papel esencial de las políticas públicas de apoyo al medio ambiente centradas en la transición energética y la financiación de las tecnologías limpias, así como de las políticas públicas de garantía destinadas a mitigar los riesgos financieros temporales de las PYMEs, derivados de la pandemia COVID 19.

Las energías tradicionales implican la emisión de gases de efecto invernadero, acentuando el problema del cambio climático. La implantación de fuentes de energía más eficientes contribuye a la sostenibilidad medioambiental y, desde el punto de vista económico, supone un aumento de la competitividad de las empresas (mayor productividad, mejor calidad de los productos, menos residuos o menor mantenimiento), lo que es especialmente importante para las PYME (Hrovatin et al., 2021; Kostka et al., 2013).

No obstante, las inversiones en tecnologías de eficiencia energética suponen un reto para las PYMEs, que se enfrentan a importantes obstáculos financieros a la hora de invertir en eficiencia energética (Kostka et al., 2013). Algunos de ellos son los riesgos técnicos, los elevados costes de inversión, la existencia de costes ocultos y la incertidumbre en torno al rendimiento de la inversión. Uno de los principales motores para promover la inversión en medidas de eficiencia energética en las pymes son las ayudas públicas, entre las que destacan las subvenciones a las pymes industriales para energías renovables, destinadas a la instalación de fuentes de energía limpias y a la sustitución de equipos industriales por alternativas más eficientes, así como los incentivos fiscales para que estas pymes adopten energías renovables.

Sin embargo, existe un vacío de información sobre las características de qué PYME industriales son más proclives a solicitarlos. En la presente tesis doctoral, a partir de una muestra de 1.992 PYMEs de la Región de Murcia (España) durante el periodo

2013-2018, se define el perfil de PYMEs potencialmente beneficiarias aplicando la metodología de random forest para muestras desequilibradas con el fin de extraer e identificar los indicadores más relevantes para dichas empresas. Una vez definido el perfil, esta información será comunicada a los organismos públicos, lo que favorecerá el diseño de convocatorias más focalizadas, contribuyendo a potenciar la eficacia de las ayudas públicas.

Los resultados muestran que los predictores más útiles para predecir qué PYMEs del sector industrial son potenciales beneficiarias de subvenciones energéticas son los relacionados con la liquidez y el endeudamiento.

Además de las ayudas públicas destinadas a la transición energética, esta tesis se centra en analizar el papel de las políticas públicas de garantía, que facilitaron el acceso al crédito de las PYME durante la pandemia de COVID 19. Las PYME suelen experimentar mayores dificultades para participar en los mercados de crédito privados debido a las asimetrías de información existentes.

La pandemia COVID-19 desencadenó graves problemas de liquidez, derivados de una caída repentina de las ventas y el volumen de negocio, y que afectaron al funcionamiento y la operativa normal de las empresas (Cressy, 2006; Ghosal & Ye, 2015). Además, esta crisis de liquidez colocó a las empresas en una situación de especial vulnerabilidad y aumentó las posibilidades de quiebra y fracaso (Lu et al., 2020). Esta difícil situación obligó a los responsables políticos de todo el mundo a enfrentarse al reto de encontrar la forma más eficaz de desplegar los fondos públicos para amortiguar los efectos negativos de la COVID-19 y limitar así, al menos parcialmente, la desaceleración de la economía (Core & De Marco, 2021).

En España, el Gobierno optó por canalizar los avales públicos a través de las entidades bancarias y puso en marcha un programa de avales públicos liderado por el ICO y gestionado por las entidades bancarias (ICO, 2020), cuyo objetivo era aumentar la liquidez de las empresas. Aunque estos avales contribuyen positivamente a reforzar la estabilidad de las PYME, una gran inyección de liquidez, como fue el caso de España, puede afectar a los niveles óptimos de endeudamiento, en particular en lo que se refiere a la deuda a largo plazo. Un crecimiento excesivo de los niveles de endeudamiento de las PYME puede conducir a una mayor inestabilidad financiera y a un grave riesgo de impago.

En la presente tesis doctoral se analiza si hubo una asignación eficiente de este programa de avales públicos. Es decir, si se dirigió hacia las PYMEs que sufrían un distress económico-financiero temporal; es decir, hacia las PYMEs que, tras el estallido de la pandemia COVID 19, tenían un mayor riesgo de impago. Las PYME que sufrieron algún tipo de dificultad antes de la pandemia COVID 19 (dificultades estructurales) no deberían haber sido beneficiarias de esas ayudas públicas porque tenderían a invertir ese dinero en proyectos muy arriesgados, aumentando así el conflicto accionista-agencia acreedora y reduciendo la asignación eficiente de esas ayudas públicas.

Nuestra muestra está compuesta por 3.305 pymes españolas, que se analizan en el periodo comprendido entre 2011 y 2020. En concreto, 2011-2017 se considera como periodo de "control" para estimar el modelo de endeudamiento óptimo, ya que la relación entre el endeudamiento óptimo y sus principales determinantes durante este periodo no se verá influenciada por las políticas intervencionistas del gobierno. Por otra parte, 2018-2020 se considera como el período principal, donde 2018 y 2019 se consideran específicamente como el «período pre-COVID» y 2020 se considera como el "período COVID". Se eligieron estos tres años porque la comparación entre 2018 y 2019 nos permite probar las variaciones prepandémicas, mientras que la comparación entre 2020 y 2019 nos permite probar las variaciones COVID.

Nuestros resultados muestran que la política intervencionista de este gobierno engrosó los niveles de exceso de deuda, principalmente debido al aumento del exceso de deuda a largo plazo, y los desvió del óptimo. Además, aunque estas garantías públicas deberían haberse destinado principalmente a las PYMEs que experimentan un declive temporal debido a la COVID-19, encontramos que estas PYMEs fueron las menos propensas a recibir inyecciones de liquidez. Por tanto, su asignación no fue eficiente, ya que no se dirigieron principalmente a las PYME que sufrieron una recesión temporal provocada por el COVID-19.

El tercer capítulo de esta tesis doctoral vuelve a estar vinculado a la importancia de las estrategias de mitigación dirigidas a reducir las emisiones de gases de efecto invernadero. El Protocolo de Kioto estableció objetivos vinculantes de reducción de emisiones de gases de efecto invernadero para los países industrializados, respondiendo a la necesidad de reducir las emisiones de gases de efecto invernadero, limitar el calentamiento global, hacer frente al cambio climático de forma eficiente y eficaz y promover el desarrollo sostenible a escala mundial.

Los mercados de carbono regulados y voluntarios son instrumentos clave para promover la reducción de las emisiones de gases de efecto invernadero. Esta tesis doctoral se centra en los mercados de carbono regulados, en los que el carbono tiene un precio y las empresas pueden reducir sus emisiones mediante el comercio de créditos de carbono. Están diseñados para cumplir los límites establecidos por los gobiernos. Los mercados regulados crean incentivos financieros para que las empresas inviertan en tecnologías y prácticas que reduzcan las emisiones. Las que emiten menos de lo permitido pueden vender sus permisos sobrantes, generando ingresos adicionales, lo que anima a las empresas a adoptar prácticas más sostenibles para reducir el coste medioambiental de sus actividades.

Dentro de los mercados regulados, el primero en crearse fue el Régimen Comunitario de Comercio de Derechos de Emisión (RCCDE) (Directiva 2003/87/CE) y se ha convertido en el mayor mercado de carbono del mundo. Estudios recientes se han centrado en analizar la conexión entre el mercado del carbono y los mercados energético, financiero y de materias primas (Adekoya et al., 2020; Arif et al., 2021; Aslan y Posch, 2022; Tiwari et al., 2022; Wang et al., 2022; Jiang y Chen, 2022; Meng et al., 2022; Suleman et al., 2023, entre otros). A diferencia de estos trabajos, el Capítulo 3 se centra en un análisis temporal y frecuencial (a corto y largo plazo) de la conectividad entre los rendimientos del RCCDE y los rendimientos de empresas europeas de bajas y altas emisiones para identificar el patrón de conectividad a lo largo de la tercera y cuarta fases del RCCDE y responder hasta qué punto la aplicación de las reformas del Régimen Comunitario de Comercio de Derechos de Emisión afecta a la conectividad entre los rendimientos de la UE y los rendimientos de empresas europeas de bajas y altas emisiones. Para ello, se aplica el índice de conectividad dinámica de Diebold y Yilmaz (2012, 2014), combinado con la descomposición de la interdependencia en bandas de frecuencia (Barunik y Krehlik, 2018).

Se utiliza una muestra de datos diarios de rendimientos de 32 empresas pertenecientes al STOXX Europe 600, 16 clasificadas como empresas de altas emisiones, con una media anual de emisiones directas de C02 equivalente sobre ingresos de 1404,52 toneladas, y las 16 restantes con una media anual de 4,03 toneladas. A partir de esta muestra, se aplica el índice de conectividad dinámica de Diebold y Yilmaz (2012, 2014), combinado con la descomposición de la interdependencia en bandas de frecuencia (Barunik y Krehlik, 2018), para medir en qué medida los shocks en EU-ETS en distintas frecuencias (a corto o largo plazo) influyen en la volatilidad de las empresas de altas y bajas emisiones.

Nuestros resultados muestran que el índice de conectividad total (TCI) entre el RCDE UE y las empresas de bajas y altas emisiones es elevado y cambiante durante el periodo de la tercera y cuarta fase del RCDE UE (de 2013 a 2024). Además, la transmisión de la volatilidad del carbono aumenta durante este periodo debido a la aplicación de las reformas del RCDE UE para acelerar la descarbonización y cumplir los objetivos climáticos de la UE. La evolución de la transmisión de la volatilidad del carbono a las empresas de bajas y altas emisiones es similar, ya que estas últimas incluyen empresas del sector financiero, que se ven muy afectadas por las perturbaciones del RCDE UE. Además, según nuestros resultados, y en consonancia con estudios anteriores, el carbono es un receptor de volatilidad, especialmente en los sectores energéticos o intensivos en energía, y la mayor parte de la conectividad se produce a corto plazo (1 día-5 días).

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INTRODUCTION

This PhD thesis presents a comprehensive exploration of the essential role of public environmental support policies focused on energy transition and clean technology financing, and public guarantee policies designed to mitigate the temporary financial risks of SMEs arising from the COVID 19 pandemic.

Traditional energies involve emitting greenhouse gasses, accentuating the problem of climate change. Implementing more efficient energy sources contributes towards environmental sustainability and, from an economic point of view, means increased company competitiveness (higher productivity, better product quality, less waste or less maintenance), which is particularly important for SMEs (Hrovatin et al., 2021; Kostka et al., 2013).

Nevertheless, investments in energy-efficient technologies are challenging for SMEs, which face which face major financial obstacles when investing in energy efficiency (Kostka et al., 2013). Some of them are technical risks, high investment costs, the existence of hidden cost and the uncertainty surrounding the return on investment. One of the main drivers to promote investment in energy efficiency measures in SMEs are public aids, including subsidies to industrial SMEs for renewable energies, aimed at the installation of clean energy sources and the replacement of industrial equipment with more efficient alternatives, as well as tax incentives for these SMEs to adopt renewable energies.

However, there is a gap of information about the features of which industrial SMEs are more likely to apply for them. In the present PhD thesis, a profile of potential beneficiary SMEs is defined applying the random forest approach for unbalanced samples to extract and identify the most relevant indicators for those companies. Once the profile is defined, this information will be reported to public bodies, what will encourage the design of more focused calls, helping to boots the effectiveness of public subsidies.

Apart from public aids aimed at energy transition, this thesis focuses on analysing the role of public guarantee policies, which facilitated access to credit for SMEs during the COVID 19 pandemic. SMEs often experience greater difficulty in participating in private credit markets due to existing information asymmetries.

The COVID-19 pandemic triggered serious liquidity problems, arising from a sudden drop in sales and turnover, and which impacted businesses' normal functioning and operating (Cressy, 2006; Ghosal & Ye, 2015). In addition, this liquidity crisis placed companies in a situation of particular vulnerability and increased the chances of bankruptcy and failure (Lu et al., 2020). This difficult situation forced policymakers worldwide to face the challenge of finding the most effective way to deploy government funds to cushion the negative effects of COVID-19 and thereby, at least partially, limit the downturn in the economy (Core & De Marco, 2021).

In Spain, the government opted to channel public guarantees through banking entities and engaged in a program of public guarantees led by the ICO and managed by banking entities (ICO, 2020), which was aimed at increasing company liquidity. Although these guarantees contribute positively to strengthening SME stability, a large injection of liquidity, as was the case of Spain, may affect optimal debt levels, in particular with regard to long-term debt. Excessive growth of SME debt levels can lead to greater financial instability and severe risk of default.

In the present PhD thesis, it is analysed if there was an efficient allocation of this program of public guarantees. That is, if it was directed towards SMEs who suffered temporary economic-financial distress; that is, towards SMEs who, after the outbreak of the COVID 19 pandemic, were at increased risk of default. SMEs who suffered any distress prior to COVID 19 pandemic (structural distress) should not have been beneficiaries of that public aid because they would tend to invest this money in very risky projects, thereby increasing the shareholder-creditor agency conflict and reducing efficient allocation of this public aid.

The third chapter of this PhD thesis is once again linked to the importance of mitigation strategies aimed at reducing greenhouse gas emissions. The Kyoto Protocol established binding targets for greenhouse gas emission reductions for industrialised countries, responding to the need to reduce greenhouse gas emissions, limit global warming, address climate change efficiently and effectively, and promote sustainable development on a global scale.

Regulated and voluntary carbon markets are key instruments to promote the reduction of greenhouse gas emissions. This PhD thesis focuses on regulated carbon markets, where carbon is priced and companies can reduce their emissions by trading carbon credits. They are designed to comply with limits set by governments. These markets create financial incentives for companies to invest in technologies and practices that lessen emissions. Those that emit less than allowed can sell their surplus permits, generating additional income, thereby encouraging businesses to adopt more sustainable practices to lower the environmental cost of their activities.

Within the regulated markets, the first one to be created was the European Union Emissions Trading System (EU-ETS) (Directive 2003/87/EC) and has become the world's largest carbon market. Recent studies have focused on analysing the connectedness between the carbon market and energy, financial and commodity markets (Adekoya et al., 2020; Arif et al., 2021; Dutta et al., 2021; Aslan and Posch, 2022; Tiwari et al., 2022; Wang et al., 2022; Jiang and Chen, 2022; Meng et al., 2022; Suleman et al., 2023, among others). Unlike previous studies that primarily focus on market indices, this chapter centers on individual high- and low-emission companies, providing a more nuanced view of how carbon markets affect different types of firms. Second, it specifically investigates how recent environmental reforms in the EU influence volatility transmission, offering valuable insights into the regulatory impact on financial markets and corporate behavior. Third, this study analyzes the evolution of volatility transmission from carbon markets over the third and fourth phases of the EU-ETS, highlighting how changes in market structure and regulatory adjustments have influenced market volatility over time. Finally, it compares the patterns of increased volatility transmission between high-emission and low-emission companies, illustrating how different levels of emissions exposure lead to varying impacts from carbon market fluctuations, which is critical for understanding the differential effects of environmental policies on firms.

In doing this, the dynamic connectivity index of Diebold and Yilmaz (2012, 2014), combined with the decomposition of interdependence into frequency bands (Barunik and Krehlik, 2018) are applied.

In relation to the structure of the present PhD thesis, it consists of three articles to achieve the general and specific objectives, which are included in chapters 1, 2 and 3, respectively. Each of these articles addresses particular aspects, providing a detailed analysis that contributes to the global understanding of the subject of study. Finally, the general conclusions of the thesis are presented. A summary in Spanish is also included.

Chapter 1: Subsidies for investing in energy efficiency measures: applying a random forest model for unbalanced samples

Investments in energy efficiency measures help companies to reduce total final energy use, improve environmental sustainability and promote business innovation, profitability, and competitiveness (Hrovatin et al., 2021).

Public financial support should be a priority of governments and public institutions for encouraging the implementation of energy efficiency measures, especially in small and medium-sized enterprises (SMEs) given that they represent the “core” of the European industrial structure and employ around 60% of the total workforce (Hrovatin et al., 2021) and they face significant barriers to implement energy efficiency measures. One potential driver should be investment subsidies since they help to reduce the up-front cost and so make the investment more profitable (Brown, 2001). In order to boost the effectiveness of these public subsidies and thereby speed up the adoption of energy efficiency measures in SMEs, it is essential for public bodies to be able to identify which businesses are potential recipients of public aid[1]. Identifying the profile of which SMEs may be potential beneficiaries of public aid poses a major challenge since this helps to design the requirements of the calls, thus favoring efficiency in channeling public funds and preventing them from remaining unused. This is also a challenge in the sense that the proportion of businesses benefiting from this public support is often very low.

The main aim of this chapter to identify the profile of industrial SMEs from the Region of Murcia (Spain) that evidence the greatest potential to invest in energy efficiency measures, handling a high volume of predictor variables (in this case, 528 indicators for each company). Identifying the profile of potential beneficiary SMEs helps governments to directly filter which SMEs might be possible beneficiaries, thereby reducing the costs (in particular, dissemination and information costs) that would be incurred by not having this profile, in addition to increasing the effectiveness of public aid allocation. Although this research is focused on the specific context of the Region of Murcia, our findings can be generalized both at the country and sector level.

[1] Throughout this chapter, we consider “potential beneficiary SMEs” to be those firms that, on the one hand, comply with the eligibility conditions to access energy efficiency aid established in the different public calls and, on the other, are also more likely to make energy investments.

By addressing this goal, we apply the random forest approach for unbalanced samples. The random forest model (Breiman, 2001, 2004) is an automatic learning technique that allows us to identify which economic and financial factors make SMEs potential beneficiaries of public investment subsidies. However, one common issue in this context is that samples are often unbalanced, since the proportion of SMEs who might benefit from receiving public subsidies is much lower than the proportion of SMEs that might not. This may yield misleading results in that while the majority group might be correctly predicted, the minority group might not. To address this issue in this chapter we apply balancing techniques to remove inefficiency from the imbalance, thereby increasing the accuracy of both the estimation and the identification of SME profile.

Our results show that the most useful predictors for predicting which SMEs are potential energy beneficiaries are related to liquidity and indebtedness. The predictor in the first position of the ranking is the ratio (related to liquidity) defined as short-term financial assets divided by net sales and captures the increase in investment capacity measured in relation to the average of the sector. Others are related to indebtedness: the ratio short-term financial debt over long-term financial debt that represents the financial debt maturity structure of a firm; the ratio that captures the percentage of long-term-debt (maturity of over one year) which is nonfinancial (other types of debt not associated with bank loans) measured in relation to the average of the sector; the ratio that captures a firm’s interest and related charges on financial debt, which are requested from banks or financial institutions; and the ratio defined as the variation ratio of a firm’s debt maturity structure measured in relation to the average of the sector.

Chapter 2: Impact of public guarantees on optimal debt levels following the COVID 19 pandemic: Efficiency in their allocation

The COVID-19 pandemic triggered a sudden drop in companies' sales and turnover, which resulted in serious liquidity and solvency problems. In terms of the economic effects, this health crisis hit financial markets as well as the activity and performance of most companies, whose sales and profits plummeted, resulting in liquidity and solvency problems (Almeida, 2021; Blanco et al., 2021; Demmou et al., 2021; He et al., 2020). In an effort to cushion these unfavorable effects, a credit guarantee plan was launched in 2020 by the the Official Credit Institute (ICO)[2] to mitigate the effects of COVID-19 by injecting firms with liquidity and/or by encouraging company investment (Blanco et al., 2021).

This credit guarantee plan was endowed with over €100,000 million to cover new loans and other forms of financing in addition to renewing the support granted by financial entities to companies and self-employed persons to meet their financing needs (ICO, 2020; *Real Decreto-Ley 25/2020, de 3 de julio, de medidas urgentes para apoyar la reactivación económica y el empleo*, 2020). Despite this public aid being led by the ICO, management thereof was conducted through the banking sector, specifically by the financial entities that voluntarily joined this program.

Over 55% of SMEs in Spain requested financial lines after the outbreak of the pandemic, and several operations were guaranteed amounting to €64,120.8 million by the end of 2020. This allowed SMEs to receive €90,221.9 million of financing to guarantee their liquidity (ICO 2020). The government's interventionist policy may have impacted debt levels since this aid may have increased SME's abnormal level of debt (by raising debt levels above optimal levels), beyond transforming said orgainizations' capital

[2] The Official Credit Institute (ICO) is a Spanish national bank linked to the Secretary of State for Economy and Business Support. It plays a three-fold role as a credit institution, an economic policy financial instrument, and as a state funding agency. For more information, visit the website: https://www.ico.es.

structure, by replacing short-term guarantees with banks for long-term public guarantees with a period of grace, a feature of his public aid for containing COVID 19.

It is vital to analyze to what extent public funding has been distributed efficiently and in accordance with the objective established by the financier, which was to inject liquidity into companies who experienced a significant decline in turnover and sales, caused exclusively by the COVID 19 pandemic (ICO, 2020). For this reason, efficient allocation of this public aid is conditional upon it being directed towards SMEs who suffer temporary economic-financial distress, i.e., towards SMEs who, after the outbreak of the COVID-19 pandemic, were at increased risk of default and/or of seeing their growth opportunities, non-debt tax shield, or financial performance negatively impacted (e.g., Abu Hatab et al., 2021; Apergis et al., 2022; Gormsen & Koijen, 2020; Padhan & Prabheesh, 2021; Sarker et al., 2022; Sun et al., 2022). Moreover, SMEs who suffered any distress prior to COVID-19 (i.e., distress considered to be structural) should not have been beneficiaries of this public aid.

This is because if this public liquidity is directed towards SMEs that suffer structural distress and which are close to bankruptcy then these SMEs would tend to invest this money in very risky projects (even those with a below zero NPV), thereby increasing the shareholder-creditor agency conflict (Ayotte et al., 2013; Chu, 2017) and reducing efficient allocation of this public aid.

In this chapter, we analyze in Spanish SMEs whether, as a consequence of the Spanish government's interventionist policy, there were changes in excess debt levels in 2020 due to the COVID 19 pandemic by comparing actual (observed) debt levels and optimal debt levels. This allows us to check how debt targets may deviate from optimal thresholds when excess liquidity is injected by governments. Additionally, we examine whether or not the allocation of public funding (mainly channeled through guarantees granted by the ICO) proved to be efficient by verifying to what degree this public aid has actually been directed towards SMEs that suffered temporary distress.

Our sample is composed of 3,305 Spanish SMEs, which are analyzed in the period between 2011 and 2020. Specifically, 2011-2017 is considered as a "control" period for estimating the optimal debt model since the relationship between optimal debt and its main determining factors during this period will not be influenced by government interventionist policies. Moreover, 2018-2020 is considered as the main period, where 2018 and 2019 are specifically considered as the "pre-COVID period" and 2020 is considered as the "COVID period". These three years were chosen because the comparison between 2018 and 2019 allows us to test pre-pandemic variations, while the comparison between 2020 and 2019 allows us to test COVID variations.

Our results show that this government's interventionist policy swelled excess debt levels, mainly due to the increase in excess long-term debt, and deviated them from the optimum. Moreover, although these public guarantees should mostly have been aimed at SMEs experiencing a temporary decline due to COVID-19, we find that these SMEs were the least likely to receive liquidity injections.

Chapter 3: Time-frequency connectivity analysis between carbon returns and the returns of high and low emitting companies

The development of carbon markets has been influenced by three key factors. Firstly, the Clean Development Mechanism (Article 12 of the Kyoto Protocol), which allows industrialised countries and companies to subscribe to agreements to meet greenhouse gas reduction targets (2008-2012) by investing in emission reduction projects in developing countries, as an alternative to acquire certified emission reductions at a lower cost than in their markets (https://www.cambioclimatico.org/). Secondly, the

European Union Emission Trading System (EU ETS), launched in 2005, which has become the world's first and largest carbon market. Finally, the voluntary carbon markets (https://www.orygen.earth/2023/07/04), which developed alongside regulated markets, allow individuals, companies, and organisations to purchase additional carbon credits, supporting projects that offset or reduce emissions.

The scheme for trading greenhouse gas emission allowances in the EU was established by Directive 2003/87/EC (European Parliament Directive 2003/87/EC), latter modified by Directive (EU) 2023/958 (European Parliament Directive (EU) 2023/958) and in Directive (EU) 2023/959 (European Parliament Directive (EU) 2023/). Directive 2003/87/EC has been crucial in EU policy to combat climate change by reducing greenhouse gas emissions in a cost-effective and economically efficient manner.

Since the beginning of the EU ETS, interest in studying carbon markets from a financial perspective has been growing. Recent studies have focused on analysing the volatility transmissions between the carbon market and financial and commodity markets, applying the dynamic connectivity index by Diebold and Yilmaz (2009, 2012, and 2014) alongside the decomposition of interdependence into frequency bands (Barunik and Krehlik, 2018) (Adekoya et al., 2020; Arif et al., 2021; Aslan and Posch, 2022; Tiwari et al., 2022; Wang et al., 2022; Jiang and Chen, 2022; Meng et al., 2022; Suleman et al., 2023, among others).

The aim of this chapter is to analyse the transmission of volatility between the returns of EU Emission Trading System (EU ETS) and returns of European companies with high and low emissions, distinguishing between short-term and long-term effects. We seek to investigate whether there is connectivity between the returns of EU ETS and of those companies, the degree of that connectivity, whether it differs between the two types of companies, and if it changes throughout the period encompassing the third and fourth phases of the EU ETS (from 2013 to 2024). We will analyse to what extent the implementation of EU ETS reforms aimed at meeting the EU's climate objectives (uncertainty regarding climate policies) affects the transmission of carbon volatility to companies in sectors traditionally classified as high-emission and low-emission. To achieve this, we apply the dynamic connectivity index developed by Diebold and Yilmaz (2009, 2012, 2014), combined with the decomposition of interdependence into frequency bands (Barunik and Krehlik, 2018), to measure the degree to which carbon shocks at different frequencies (short or long term) influence the returns of high- and low-emission companies.

We use daily data of returns of 32 companies belonging to STOXX Europe 600, for the period 01/01/2013-30/04/2024. Data are collected from Eikon Datastream. Out of the 32 companies, 16 are classified as high-emission companies, with an annual mean of direct C02 equivalent emissions over revenues of 1404.52 tonnes, while the remaining 16 are low-emission companies, with an annual mean of 4.03 tonnes. The study period encompasses the third (2013-2020) and fourth phases (2021-2030) of the EU ETS (from 2013 to 2024). It has been divided into three subperiods, according to relevant events to see if the connectivity of the EU ETS returns with the returns of high and low-emission companies is also affected. Specifically, in 2018, there was a rise in CO2 prices due to various reasons, primarily the entry into force of the reform of the EU Emissions Trading System, which included a reduction in the supply of emission permits following the approval of the Market Stability Reserve (EU, 2018). In 2020, the key event was the official withdrawal of the United States from the Paris Agreement on climate change on 4 November 2020. On 19 February 2021, the United States signed again the Paris Agreement following Biden's assumption of the presidency.

Our results show that the connectivity between the EU ETS returns and returns of high- and low-emitting European companies is high and changing over the third and fourth phases of the EU ETS (from 2013 to 2024): 81.4% from 01/01/2013 to 31/12/2017; 77.7% from 01/01/2018 to 30/10/2020; and 75.15% from 02/11/2020 to 30/04/2024. Specifically, carbon volatility transmission increases over this period due to the implementation of EU ETS reforms to accelerate decarbonisation and achieve the EU climate objectives: in the third sub-period it is equal to 28.41%, compared to 20.15% in the second sub-period and 14.79% in the first sub-period. It has approximately doubled. The evolution of carbon volatility transmission to high and low emitting companies is similar, as the latest include companies in the finance sector, which are highly affected by shocks in the EU ETS: from 9.82% to 17.83% for the subsample of high-emitting companies and from 11.96% to 21.71% for the subsample of low-emitting companies. Moreover, according to our results, and in line with previous studies, carbon is a volatility receiver, especially in energy or energy-intensive sectors, and most of the connectivity occurs in the short term (1 day-5 days): -33.87%, -27.44% and -26.31%, in the first, second and third sub-period, respectively.

CHAPTER 1

SUBSIDIES FOR INVESTING IN ENERGY EFFICIENCY MEASURES: APPLYING A RANDOM FOREST MODEL FOR UNBALANCED SAMPLES

An earlier version of this chapter was presented at the following conference: V Jornadas de Doctorado y Seminarios Novel del programa de Doctorado DEcIDE (2020), VI Congreso Iberoamericano de Jóvenes Investigadores en Ciencias Económicas y Dirección de Empresas (2023) and research prize in accounting and finance.

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ABSTRACT

Investing in energy efficiency measures is a major challenge for SMEs, both for environmental and economic reasons. However, certain barriers often make it difficult to invest in such measures. Although public financial support helps to overcome economic barriers, public bodies face the challenge of identifying which SMEs display the greatest potential to invest in energy efficiency measures. By applying a random forest technique and by using sampling balancing techniques, this chapter identifies the profile of industrial SMEs that might be potential beneficiaries of public aid, thereby helping public institutions to target their calls and direct their efforts towards this group of SMEs. Specifically, liquidity and indebtedness are found to be the most useful predictors for SMEs in the industrial sector. The results are robust and reveal that applying a random forest approach for unbalanced samples offers greater predictive capacity and statistical power than applying traditional estimation techniques. By identifying potentially benefiting firms, this work helps to boost the effectiveness of public subsidies and to improve the channeling of public funds, which ultimately favors investment in energy efficiency.

1.1. INTRODUCTION

Investments in energy efficiency measures offer companies many advantages. They not only help to reduce total final energy use[1] and to improve environmental sustainability but also promote business innovation, profitability, and competitiveness (Hrovatin et al., 2021). Governments should promote these investments, especially in small and medium-sized enterprises (SMEs) given that the latter represent the "core" of the European industrial structure and employ around 60% of the total workforce

[1] Throughout this chapter, we consider "energy use" to be all the final energy supplied to industry (regardless of the energy source) (CARM, 2019).

(Hrovatin et al., 2021), thereby making them a special focus for investments in energy efficiency. However, SMEs are less likely to invest in such efficiency measures compared to large companies (Cagno et al., 2017; Kostka et al., 2013). Implementing energy efficiency measures thus remains a pending issue for SMEs, with many still reluctant to invest in them (Trianni & Cagno, 2012). In fact, over two thirds of these businesses do not implement even the simplest rules to manage energy use (Cagno et al., 2015).

Several barriers[2] make these SMEs less likely to implement energy efficiency measures. Among these obstacles, firm size is one of the main factors influencing the adoption of energy efficiency measures, thereby evidencing that such efficiency has not been a priority for SMEs –especially those that lack energy-intensive production processes (Cagno et al., 2010; Thollander et al., 2013). Being smaller also means that these organizations have fewer technological options to save energy (Cagno et al., 2010). Moreover, there are other barriers related to information asymmetries as well as hidden and transaction costs, added to which capital restrictions tend to be more prevalent for SMEs when compared to larger companies (Nehler et al., 2018; Trianni & Cagno, 2012). Fleiter et al. (2012) and Trianni et al. (2016) highlight that economic and financial factors (specifically, lack of capital to face up-front costs) constitute important barriers that SMEs face when seeking to adopt energy efficiency measures.

Considering this context, governments and public institutions face an important challenge when designing and implementing public policies aimed at minimizing the barriers that prevent energy-efficient measures from being adopted (Prasad Painuly, 2009). Public financial support should thus be a priority for encouraging the implementation of energy efficiency measures, with investment subsidies being one

[2] A barrier is defined as “a postulated mechanism that inhibits investment in technologies that are both energy efficient and (apparently) economically efficient” (Carlander & Thollander, 2023, p. 2), emphasizing the importance of the "cost-effective" factor (Sorrell et al., 2004).

potential driver[3] since they help to reduce the up-front cost and so make the investment more profitable (Brown, 2001). In order to boost the effectiveness of these public subsidies –and thereby speed up the adoption of energy efficiency measures in SMEs– it is essential for public bodies to be able to identify which businesses are potential recipients of public aid[4]. Identifying the profile of which SMEs may be potential beneficiaries of public aid poses a major challenge since this helps to design the requirements of the calls, thus favoring efficiency in channeling public funds and preventing them from remaining unused. This is also a challenge in the sense that the proportion of businesses benefiting from this public support is often very low.

In an effort to fill this key gap, this chapter aims to identify the profile of those SMEs that evidence the greatest potential to invest in energy efficiency measures. We apply the random forest approach for unbalanced samples so that –based on this identification– public institutions can direct public investment subsidies towards the group of businesses identified. For this purpose, a sample of industrial SMEs from the Region of Murcia (Spain) is used. These provide the focus of the study because the public call analyzed in this research deals exclusively with these companies since they represent over 25% of final energy consumption in Spain. It is therefore important to carry out improvements in energy efficiency in technologies and processes and in terms of implementing energy management systems in this context.

By addressing this goal, the contributions made by this chapter can be grouped into the following blocks. At a methodological level, this article applies the random forest approach for unbalanced samples. The random forest model (Breiman, 2001, 2004) is an

[3] Drivers are defined as "factors stimulating the sustainable adoption of energy-efficient technologies, practices and services, influencing a portion of the organization and a part of the decision-making process in order to tackle the existing barriers" (Trianni et al., 2017, p. 204).
[4] Throughout this study, we consider "potential beneficiary SMEs" to be those firms that, on the one hand, comply with the eligibility conditions to access energy efficiency aid established in the different public calls and, on the other, are also more likely to make energy investments.

automatic learning technique that allows us to identify which economic and financial factors make SMEs potential beneficiaries of public investment subsidies. However, one common issue in this context is that samples are often unbalanced –since the proportion of SMEs who might benefit from receiving public subsidies is much lower than the proportion of SMEs that might not. This may yield misleading results in that while the majority group might be correctly predicted, the minority group might not. To address this issue in a novel way, this chapter applies balancing techniques to remove inefficiency from the imbalance, thereby increasing the accuracy of both the estimation and the identification of SME profile. Furthermore, this chapter offers some evidence that applying a random forest approach for unbalanced samples offers greater predictive capacity and statistical power than applying traditional estimation techniques within this research field. At the context level, this chapter focuses on the Region of Murcia, which allows us to carry out a homogeneous analysis of the requirements that SMEs must fulfil in order to apply for public investment subsidies, thereby making it possible to establish an accurate profile of potential SME beneficiaries. This is an advantage compared to previous studies that analyze various contexts –in which legislative, fiscal, and context aspects may vary– and which may ultimately affect the eligibility of the industrial SMEs that can opt for public subsidies (for further information about this context, see Section 2). Finally, at a practical level, public agents are provided with the profile of the industrial SMEs to which they should direct their actions (specifically, as regards designing, implementing, and disseminating their public subsidies) in an effort to therefore maximize investment in energy efficiency measures. In addition to proving useful for public institutions in the Region of Murcia, the resulting profile is also useful for contexts and sectors similar to the one analyzed in this chapter.

The chapter is structured as follows. After this introduction, Section 2 describes the most relevant particularities of the context of the Region of Murcia. Section 3 reviews the literature on the main barriers facing SMEs who seek to invest in energy efficiency measures, as well as the role of public subsidies as an instrument to promote these investments. In Section 4, we address all the methodological aspects (sample, data, variables) in addition to describing the random forest approach used and the techniques applied to control for unbalanced samples. The results are presented in Section 5. Finally, Section 6 offers the discussion of the findings, and Section 7 contains the concluding remarks.

1.2. THE REGION OF MURCIA

The Region of Murcia in southeast Spain is a region in the Mediterranean area of the Iberian Peninsula. Covering an area of around 11,300 square kilometers, this region combines a diversity of landscapes, ranging from the coast bathed by the Mediterranean to the inland mountains. At an economic level, the Region of Murcia has experienced significant development in recent years, with agribusinesses and the wine industry standing out in particular. In terms of energy efficiency, the Region of Murcia faces challenges common to many other regions in Spain. Diversification of the energy matrix and the transition towards more sustainable energy sources are key areas of interest. Given its location in a region that enjoys abundant sunlight, energy efficiency can benefit from promoting solar technologies and other renewable energy sources.

Opting for the Region of Murcia as the context for this chapter is relevant for three main reasons. Firstly, Spain is divided into different regions whose regional policies and regulations tend to differ. This means that the public calls for investment subsidies tend to vary between regions to the extent that these calls and formalities depend directly on each regional government. In order to achieve consistency in the sample and so obtain conclusive results, we focus on a single region, thereby ensuring that the regional policy and regulation applicable to all SMEs included in the study is the same. In the specific case of the Region of Murcia, the energy subsidy analyzed seeks to compensate a specific percentage of the investment made by each SME in energy efficiency measures (CARM, 2019), with industrial SMEs that meet the eligibility requirements being those that can apply for said subsidy (further information about this subsidy is provided in Section 4.2).

Secondly, most energy consumption in Spain is focused on industrial sector and on electrical energy. As shown in Table 1, Spain's energy consumption amounted to €11,227 million in 2019, of which €6,368 million was electrical energy and €3,371 million gas. In the Region of Murcia, energy consumption came to €438.6 million in 2019, and there was a similar distribution between the different energy sources (Spanish National Statistics Institute, 2019). Moreover, the industrial sector represents over 25% of energy consumption (CARM, 2019), such that special attention must be paid to this sector in order to encourage the implementation of more energy efficiency measures. More specifically, the energy consumption based on the NACE Rev 2 codes is shown in Appendix A, where both the relevant weight that the industrial sector has in energy consumption and the distribution of energy sources based on the NACE Rev 2 code can be seen. Energy efficiency investments focused on electrical energy are therefore especially relevant in Spain as a whole and in the Region of Murcia in particular. In fact in 2021, Spain was the second country in the European Union in terms of generating the most electrical energy from wind and solar sources (Red Eléctrica, 2022), with the Region of Murcia being one of the leading areas in terms of photovoltaic solar energy generation.

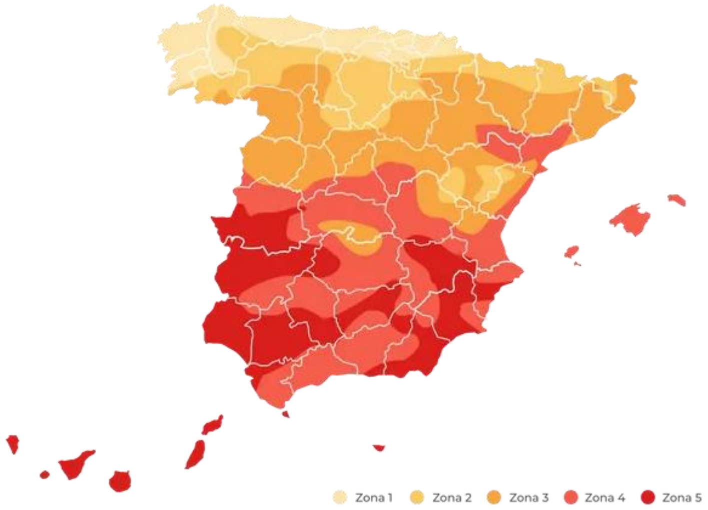
Table 1. Distribution of energy consumption in Spain and the Region of Murcia (2019)

	Electricity	Gas	Diesel	Fuel oil	Coal and coke	Biofuels	Heat and others	Total
Spain	6367.9	3371.3	678.3	99.1	104.6	44.7	560.8	11227.0
	56.72%	30.03%	6.04%	0.88%	0.93%	0.40%	5.00%	100.00%
Region of Murcia	209.6	128.7	24.3	2.3	0.7	0.5	465.3	438.6
	47.79%	29.35%	5.53%	0.53%	0.15%	0.11%	5.09%	100.00%

Note: The figures are expressed in millions of euros.
Source: Spanish National Statistics Institute.

Thirdly, Murcia is one of the European regions with the greatest number of hours of sunshine per year. A recent study into "the Sunniest Cities in Europe" classifies the area of Murcia as the third sunniest city, with an average of 346 hours of sun per month (Holidu, 2022). Considering that the power generation capacity of photovoltaic energy is mostly influenced by solar radiation intensity (which is quite high in the Region of Murcia, as shown in Figure 1), investing in energy efficiency measures (especially solar) is of particular interest in the Region of Murcia. The amount of sunlight in a region like this tends to impact the attractiveness of energy efficiency projects (e.g., due to solar energy potential, economic viability, energy independence, renewable energy targets), and to influence government decisions regarding public subsidies. Regions with ample sunlight are thus likely to receive more support since they offer a more viable and efficient option for investing in energy efficiency measures (e.g., by harnessing clean and renewable energy).

Figure 1. Solar radiation map in Spain (2023)



Note: The map of solar radiation in Spain is divided into five zones according to the incidence of the sun on the surface. Types of radiation are differentiated according to the ray and its incidence, and the measuring equipment is the pyranometer.
Source: Soto (2023).

In sum, the Region of Murcia offers a unique combination of geographical and economic characteristics, thus making it an interesting context in which to explore strategies and solutions in the field of energy efficiency. In this way, the regional government plays a key role in encouraging these investments through public aid –which encourages higher levels in cost reduction and in return on investment.

1.3. LITERATURE REVIEW

Ever-increasing global competitiveness makes companies place greater emphasis on improving their efficiency and –since most of their processes are related to energy– any such improvements in energy efficiency will enhance this (Nehler et al., 2018). Investing in energy efficiency measures is thus a major concern for organizations for two main reasons. From an environmental point of view, traditional energies involve emitting harmful gases –specifically greenhouse gases (GHG)– into the atmosphere, thereby accentuating the problem of climate change. Added to this is the uncertainty surrounding the availability of these traditional energy sources (Cagno et al., 2013). Implementing more efficient energy sources therefore contributes towards environmental sustainability. In addition, from an economic point of view, implementing energy efficiency measures means increased company competitiveness –which is particularly important for SMEs (Hrovatin et al., 2021; Kostka et al., 2013)– such that these measures yield cost savings and entail the modernization and innovation of firms' energy sources. Beyond the energy benefits derived from investing in these measures (such as energy savings, energy costs, environmental improvements), the non-energy benefits (such as higher productivity, better product quality, less waste, or less maintenance) also stand out (Nehler et al., 2018), all of which positively impacts financial performance.

However, investments in energy-efficient technologies are still limited by the hurdles and market failures that prevent the most energy-efficient alternative from being chosen, even if this alternative is the most profitable for organizations (Fleiter et al., 2011). This is particularly true for SMEs, for whom investments in energy efficiency are often considered "low priority" projects (Fleiter et al., 2012). In addition, such firms must also face more difficult obstacles when investing in energy efficiency (particularly, in the financial field) (Kostka et al., 2013). All of this creates a "gap" between the theoretical opportunities for cost-effective investments in energy efficiency and the actual levels that may be achieved in practice (Cagno et al., 2013; Hirst & Brown, 1990; Sudhakara Reddy, 2013). In this context, "barrier models" have been the widely accepted framework for explaining the existence of the energy efficiency gap (Backlund et al., 2012; Jaffe & Stavins, 1994a). These barriers can differ substantially in nature, and several studies have stated different but related taxonomies. For instance, (i) Cagno et al. (2013) establish seven categories of barriers, including *technology-related*, *information-related*, *economic*, *behavioral*, *organizational*, *competence-related*, and *awareness*; (ii) Sorrell et al. (2004) classify these barriers into the following six categories, including *imperfect information*, *hidden costs*, *risk*, *access to capital*, *split incentives*, and *bounded rationality*; while (iii) Kostka et al. (2013) establish three large groups of barriers, i.e. *financial*, *information*, and *organizational* barriers.

Regardless of the taxonomy used, economic-financial barriers are one of the main obstacles stated by most previous literature when seeking to implement energy efficiency measures (Prasad Painuly, 2009), especially in an SME context (Kostka et al., 2013). Among the main economic-financial factors that prevent investment in efficient energy, the literature states technical risks (Brunke et al., 2014; Thollander et al., 2013), high investment costs (Fleiter et al., 2012; Hrovatin et al., 2021), the existence of hidden costs (Cagno et al., 2013), or uncertainty surrounding the return on investment (Harris et al., 2000; Thollander et al., 2013). In addition, access to capital proves key, given that companies often lack sufficient capital to invest in energy efficient technologies (e.g., Enrico Cagno & Trianni, 2013; Fleiter et al., 2012; Hrovatin et al., 2021; Thollander et al., 2007).

Limitations on access to capital not only refer to the external capital that companies may obtain from banking institutions (where SMEs have greater difficulty raising funds when compared to large organizations) but also to the use of internal capital and to establishing priorities among alternative investment projects (Fleiter et al., 2011). Fleiter et al. (2012) state that the lack of capital proves to be a major obstacle that slows down the adoption of energy efficiency measures. Similarly, Kostka et al. (2013) find that companies fail to make possible investments in energy efficiency improvements because they cannot access the required investment capital at competitive prices. We therefore see how these economic-financial barriers (in particular, access to capital limitations) lie behind these low figures for investment in energy efficiency measures, and how they prevent companies (specifically SMEs) from taking advantage of the economic and energy benefits that could be derived were they to invest in them.

To counteract the above barriers or obstacles, there are several drivers that make investments in energy efficiency measures more attractive and profitable for companies. Trianni et al. (2013) identify four large groups of drivers that can favor investments: *regulatory*, *economic*, *informative*, and *vocational training*. Among these, the literature has highlighted economic drivers as the ones that display the greatest potential and effectiveness for reducing economic-financial barriers (Cagno et al., 2017; Thollander et al., 2013; Trianni et al., 2016). Indeed, Hrovatin et al. (2021) affirm that economic drivers would top the list in importance in SMEs vis-à-vis effectively promoting investments in efficient energy. These economic drivers include the cost reduction stemming from lower energy use, information about real costs, management support, public aid, or private financing (Cagno et al., 2015; Trianni et al., 2013).

Among these drivers, public aid plays a crucial role in promoting investment in energy efficiency measures, with government intervention proving useful for overcoming the market failures that impede the efficient allocation of resources towards energy-saving initiatives (Jaffe & Stavins, 1994b). Public aid aimed at promoting investment in efficiency energy measures often varies by country –and even by region– and may take different forms, such as subsidies, tax incentives, grants, and regulatory support. For instance, production tax credits (PTCs) and investment tax credits (ITCs) are provided by the United States government to encourage the development of renewable energy projects (Dwivedi, 2018); green bonds are other public financial instruments specifically earmarked to raise funds for environmentally friendly projects (Zhao et al., 2022); feed-in tariff programs are implemented by several countries where renewable energy producers are paid a fixed rate for the electricity they generate (Bertoldi et al., 2013); and grants and subsidies are a common type of public aid that provide direct financial support that can be used for project development, equipment purchase, or other eligible expenses (Yang et al., 2019).

In this context, public subsidies have attracted considerable attention from academia as they are a major driver for improving energy efficiency worldwide (Allcott & Greenstone, 2012; Gillingham et al., 2009; Nie et al., 2017). These subsidies can make investments more attractive and economically profitable, in addition to favoring cost reduction through reduced energy use (Brunke et al., 2014; Cagno et al., 2015). Public subsidies also emerge as an effective policy measure to accelerate the dissemination of energy efficiency measures in SMEs (de Groot et al., 2001; Fleiter et al., 2012). Given the importance of these firms for the economy, if governments are to actively encourage energy efficiency investment in SMEs then they should target their subsidy policies towards such companies (Yang et al., 2019).

Both fixed and output subsidies coexist globally (Nie et al., 2017). While fixed subsidies offer a predetermined amount of assistance, output subsidies are linked to the quantity of goods or services produced. Governments often implement these subsidies simultaneously in order to provide financial support to various industries (Nie et al., 2017). Such a dual approach allows governments to address different economic objectives, encourage growth, and support specific sectors through tailored subsidy mechanisms.

Moreover, these public investment subsidies are highly correlated with private financing (Cagno et al., 2017) and reflect the need for companies to receive external economic support, either from public and/or private agents. In this vein, the role of governments is vital when designing and implementing certain policies or measures (such as these public subsidies) geared towards correcting market failures and reducing obstacles/barriers to investment (Prasad Painuly, 2009). Nevertheless, the challenges and nuances involved in the effectiveness of this public aid are also acknowledged in the literature in the sense that justifying the differing degrees of government intervention remains a controversial topic in previous studies (see Sudhakara Reddy, 2013). For government intervention to be effective, it is necessary to direct public incentives towards those SMEs that exhibit the greatest potential to invest in energy efficiency measures. In fact, caution against blanket subsidies should be taken into account, with the argument being that poorly designed policies may lead to inefficiencies and unintended consequences (Allcott & Greenstone, 2012). It is important to carefully craft interventions that consider market dynamics and company behavior so as to maximize the effectiveness of public aid. Well-designed public policies thus prove pivotal to effectively driving the adoption of energy-efficient measures, and thereby contributing to overall sustainability goals.

Given the existing literature on energy efficiency measures, two issues need to be resolved relating to public subsidies as one of the main drivers of these measures. Firstly, despite the importance of targeted subsidies, there is no accurate information about the features of which industrial SMEs are more likely to apply for them. This failure means that public calls are often far from reality and that the channeling of this public aid proves ineffective. This also implies that the barriers which prevent the implementation of energy efficiency measures are not overcome, leading SMEs to remain reluctant to make these investments (Trianni & Cagno, 2012). Secondly, defining the required profile is also difficult due to two methodological issues: (i) the proportion of SMEs that usually apply for public subsidies is very small, which generates an imbalance in the sample that can negatively affect the power of estimation; and (ii) there are many determinants behind the SME's decision to apply or not for the subsidy, with traditional models simply tending to consider a limited number of indicators in their estimations. If these issues are not adequately addressed, the results may be biased, and it will not be possible to predict an adequate profile of SMEs who may potentially benefit from these public subsidies.

This chapter thus seeks to narrow these gaps by offering progress in the following areas:

- Defining a profile of potential beneficiary SMEs in order to report the information to public bodies so that they can take it into account when designing, implementing, and disseminating their public policies. This profile will encourage the design of more focused calls, thereby ultimately helping to boost the effectiveness of public subsidies and the number of investments in energy efficiency measures (generating, in turn, the environmental and economic benefits mentioned at the beginning of this section).
- Moving forward by implementing more sophisticated prediction techniques that allow a number of indicators to be managed and by addressing sample imbalance, thereby offering more accurate and robust results. This is materialized by applying the random forest approach for unbalanced samples. Specifically, the first step is to apply the sample balancing technique to achieve a certain balance between the proportion of SMEs that apply for a public investment subsidy and those that do not. The random forest approach then allows several independent decision trees to be created, considering a wide array of economic and financial indicators. Based on all the decision trees, the most relevant indicators for those companies who are most likely to apply for the subsidy are then extracted and identified.

1.4. METHODOLOGY

1.4.1. Sample and data

Our sample comprises a subset of SMEs, analysis of whom is key within the energy efficiency-related field because these organizations –in addition to representing the majority of the productive fabric worldwide (Hrovatin et al., 2021)– tend to implement few energy efficiency measures (Cagno et al., 2017; Kostka et al., 2013). For this reason, public efforts should focus on SMEs in an effort to change this undesirable trend and increase SME competitiveness. Following European Commission Regulation No. 651/2014, we consider SMEs to be organizations that meet the following three requirements: (a) businesses with less than 250 employees; (b) businesses whose annual turnover does not exceed €50 million; and (c) businesses whose assets do not exceed €43 million (European Commission, 2014).

We specifically took SMEs included in the SABI (*Iberian Balance Analysis System*) database, but applied a double filter. Firstly, we only include SMEs located in the Region of Murcia (Spain), for the reasons highlighted in Section 2. Secondly, we only include those SMEs that meet all the requirements (or eligibility conditions) stated in the "Order of the Regional Ministry of Employment, Universities, Business, and the Environment of the Region of Murcia", which establishes the regulatory bases of the aid program for energy efficiency actions (CARM, 2019). Based on this call, we include SMEs that fall within the NACE Rev 2 codes shown in Table 2. Basically, the industrial sector was the one for which the 2019 call for public subsidies was set up. The industrial sector comprises firms engaged in the manufacturing and production of capital goods such as construction, machinery or chemical products, among others. Any SMEs in a crisis situation were also excluded.

Table 2. NACE Rev 2 codes included in the sample

Code	Definition
07	Mining of metal ores
08	Other mining and quarrying
09	Mining support service activities
10	Manufacture of food products
11	Manufacture of beverages
13	Manufacture of textiles
14	Manufacture of wearing apparel
15	Manufacture of leather and related products
16	Manufacture of wood and of products of wood and cork
17	Manufacture of paper and paper products
18	Printing and reproduction of recorded media
19	Manufacture of coke and refined petroleum products
20	Manufacture of chemicals and chemical products
21	Manufacture of basic pharmaceutical products and pharmaceutical preparations
22	Manufacture of rubber and plastic products
23	Manufacture of other non-metallic mineral products
24	Manufacture of basic metals
25	Manufacture of fabricated metal products, except machinery and equipment
26	Manufacture of computer, electronic and optical products
27	Manufacture of electrical equipment
28	Manufacture of machinery and equipment
29	Manufacture of motor vehicles, trailers, and semi-trailers
30	Manufacture of other transport equipment
31	Manufacture of furniture
32	Other manufacturing
33	Repair and installation of machinery and equipment
35	Electricity, gas, steam, and air conditioning supply
36	Water collection, treatment, and supply
37	Sewerage
38	Waste collection, treatment, and disposal activities; materials recovery
39	Remediation activities and other waste management services

After applying this double filter –and after excluding SMEs for which there is no information available for all the years– our sample came to 1,992 industrial SMEs, which are analyzed in the period between 2013 and 2018. This period was selected because the call for public subsidies was published in 2019 by the regional government of Murcia, and because compliance with the requirements for SMEs to benefit from public aid had to be accredited prior to the publication date of the call.

The data used for this study are extracted directly from the SABI database. More specifically, SABI offers information on all economic-financial predictors, in addition to providing information on which SMEs applied for an energy efficiency subsidy in 2019 (there is an "observations" section within the subsidies where the specific type of subsidy received can be coded).

1.4.2. Variables

Dependent variable. Initially, we collected the data from the SABI database on whether an SME had applied or not for an energy efficiency subsidy in 2019. Based on this information –and using artificial intelligence techniques to solve a classification problem– we sought to estimate the probability that an SME would request or not a public investment subsidy in the future, where the group of SMEs likely to request the public subsidy is really the one of interest. This variable is thus dichotomous, taking the value 1 if the SME does request a public subsidy, or the value 0 if the SME does not.

In the public call analyzed in this chapter, the subsidy is calculated as a percentage of the investment costs –specifically, 30% of the investment in energy efficiency measures, considering the limits stated in the public call (CARM, 2019). The investment must be directly related to energy savings and efficiency, i.e. the subsidized investment must be aimed at implementing efficient technology. The aid granted by the regional government is co-financed with contributions from the European Regional Development Fund (ERDF). Only those SMEs that previously met the eligibility requirements established in the call could apply for these public subsidies –in particular, only SMEs included in any of the NACE Rev 2 codes indicated in the call –in the industrial sector– could apply.

Predictor variables. We include 88 economic and financial indicators (ratios) related to indebtedness, investment, personnel expenditures, dividend policy, liquid assets, and other current assets and liabilities, as shown in Table 3. In general, those indicators related to indebtedness and liabilities are expected to have a negative effect on the probability of applying for this public aid to invest in energy efficiency, since indebtedness and liabilities tend to reduce a company's investment capacity. For their part, indicators related to assets, dividends, liquidity, or size are expected to have a positive effect. Based on these 88 indicators, the dataset used in random forests consists of 528 indicators, formed as follows: (i) the corresponding value of the ratio for 2018 (R*number*); (ii) the variation rate of each ratio between 2017 and 2018 (VR*number*); (iii) the year-on-year growth rate of each ratio over the period 2013-2018 (GR*number*); (iv) industry-relative indicators in terms of the value for 2018 (IR*number*); (v) industry-relative indicators in terms of the 2017-2018 variation rate (IVR*number*); and (vi) industry-relative indicators in terms of the 2013-2018 year-on-year growth rate (IGR*number*). As can be seen, the large volume of indicators (specifically, 528 indicators for each company, implying over one million observations) does not allow for the application of regression or discriminant analysis models in which the number of parameters would eliminate the degrees of freedom of the model. In addition, linear models based on multiple discriminant analysis or logistic regression would require prior selection of the explanatory variables, which would cancel out the option of creating decision trees.

Table 3. Economic and financial indicators

Indebtedness	**Expected sign**	**Indicators**
Total indebtedness	–	**R1**: Total debt/Total equity and debt; **R2**: Total equity/Total equity and debt; **R3**: Financial debt/Total equity and debt; **R4**: Financial debt/Total debt; **R5**: Non-financial debt/Total equity and debt; **R6**: Non-financial debt/Total debt
Long-term indebtedness	–	**R7**: Long-term financial debt/Total debt; **R8**: Long-term financial debt/Long-term debt; **R9**: Long-term financial debt/Total equity and debt; **R10**: Long-term debt/Total equity and debt; **R11**: Long-term debt/Total debt; **R12**: Long-term non-financial debt/Total debt; **R13**: Long-term non-financial debt/Total equity and debt; **R14**: Long-term non-financial debt/Long-term debt
Short-term indebtedness	–	**R15**: Short-term financial debt/Total debt; **R16**: Short-term financial debt/Short-term debt; **R17**: Short-term financial debt/Total equity and debt; **R18**: Short-term debt/Total equity and debt; **R19**: Short-term debt/Total debt; **R20**: Short-term non-financial debt/Total debt; **R21**: Short-term non-financial debt/Total equity and debt; **R22**: Short-term non-financial debt/Short-term debt; **R23**: Short-term debt/Long-term debt; **R24**: Short-term financial debt/Long-term financial debt
Financial expenses (and incomes)	–	**R25:** Financial expenses/Total equity and debt; **R26**: Financial expenses/Total debt; **R27**: Financial expenses/Financial debt; **R28**: Financial expenses/Net sales; **R29**: Financial incomes/Total assets; **R30**: Financial incomes/Net sales; **R31**: (Financial incomes-Financial expenses)/Total assets; **R32**: (Financial incomes-Financial expenses)/Net sales; **R33**: (Financial incomes-Financial expenses)/Earnings before interest and taxes; **R34**: Financial expenses/Earnings before interest and taxes
Investment		**Indicators**
Non-current assets	+	**R35**: Tangible assets/Total assets; **R36**: Tangible assets/Non-current assets; **R37**: Non-current financial assets/Total assets; **R38**: Non-current financial assets/Non-current assets; **R39**: Investment property/Total assets; **R40**: Investment property/Non-current assets; **R41**: Non-current assets/Total assets
Other non-current assets	+	**R42**: Other non-current assets/Non-current assets; **R43**: Other non-current assets/Total assets; **R44**: Total equity/Non-current assets
		Indicators
Personnel expenses	+	**R45**: Personnel expenses/Net sales; **R46** (Personnel expenses/Other operating expenses); **R47** (Personnel expenses/Number of employees); **R48**: Personnel expenses/Non-current assets

Employees	+	**R49**: Number of employees/Net sales; **R50** (Number of employees/Other operating expenses); **R51**: Number of employees/Non-current assets
Dividend policy		**Indicators**
Dividends and reserves	+	**R52**: Total ordinary dividends/Net income; **R53**: Reserves/Total equity; **R54**: Reserves/Total equity and debt; **R55**: Reserves/Net income; **R56**: Reserves/Non-current assets
Liquid assets (cash holdings)		**Indicators**
Cash	+	**R57:** Cash/Total assets; **R58**: Cash/Current assets; **R59**: Cash/Short-term debt; **R60**: Cash/Net sales
Cash and cash equivalents	+	**R61:** Cash and cash equivalents/Total assets; **R62**: Cash and cash equivalents/Current assets; **R63**: Cash and cash equivalents/Short-term debt; **R64**: Cash and cash equivalents/Net sales
Other current assets and liabilities		**Indicators**
Current assets	+	**R65**: Current assets/Total assets; **R66**: Current assets/Short-term debt; **R67**: (Current assets-inventories)/Short-term debt; **R68**: (Current assets-inventories-trade receivables)/Short-term debt; **R69**: (Current assets-Short-term debt)/Net sales; **R70**: Current assets/Non-current assets
Inventories	+	**R71:** Inventories/Total assets; **R72**: Inventories/Current assets; **R73**: Inventories/Short-term debt; **R74**: Inventories/Net sales; **R75**: (Inventories/Supplies)*365; **R76**: (Inventories+trade receivables)/Trade payables
Trade receivables	+	**R77:** Trade receivables/Total assets; **R78**: Trade receivables/Current assets; **R79**: Trade receivables/Short-term debt; **R80**: Trade receivables/Net sales; **R81**: Trade receivables/Trade payables; **R82**: (Trade receivables/Net sales)*365
Short-term financial assets	+	**R83:** Short-term financial assets/Total assets; **R84**: Short-term financial assets/Current assets; **R85**: Short-term financial assets/Short-term debt; **R86**: Short-term financial assets/Net sales
Trade payables	–	**R87:** Trade payables/Net sales; **R88**: (Trade payables/supplies)*365

The selection technique used to identify the economic-financial indicators is preprocessing, which refers to all the transformations on the raw data into a structured data set before it is fed into the machine learning (Kuhn & Johnson, 2013). This is a crucial part of data analytics prior to modeling since data preparation affects the model's predictive capacity. After removing missing values, the preprocessing step that we followed was data reduction, which was aimed at removing redundant and irrelevant predictors. This was done carefully in order to ensure that no predictive information was lost and that no erroneous information was added to the data. This allowed us to obtain a more reduced representation of the predictors, which was smaller in volume but which produced almost the same analytical results. This dimensionality reduction helped to speed up training. We also carried out a preliminary selection of predictors based on the correlation matrix, which shows the relation between two given predictors in the form of a matrix. Specifically, we used the correlation matrix to reduce dimensionality because one of the assumptions in most key machine learning models is that no variable in the model is highly correlated to any other variable. We thus built the correlation matrix for predictors to test correlation between independent variables.

1.4.3. Random forest approach for an unbalanced sample context

We build a model to classify firms which have or have not applied for a financial subsidy to improve energy efficiency, based on their characteristics. Specifically, we develop a random forest model (Breiman, 2001, 2004) on a synthetically balanced training dataset to build a classifier for our study; i.e., to classify whether a firm has applied for a financial subsidy or not to improve energy efficiency (for instance, in terms of installing energy-efficient facilities, improving technology in equipment and industrial processes, or implementing energy management systems). In this case, we face a problem with unbalanced classification, where there are few cases in the minority class or positive class (i.e., firms which have applied for a financial subsidy), while most cases belong to the majority class or negative class (i.e., firms which have not applied for a financial subsidy).

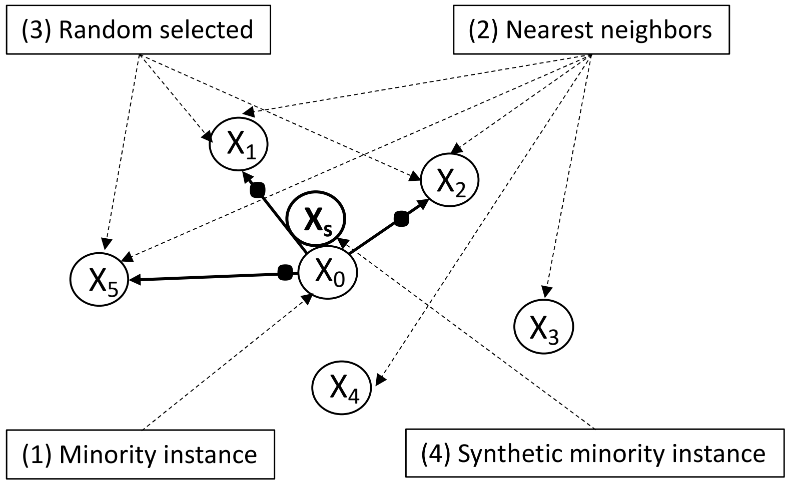
The minority class in our study is the most important, as usually occurs in learning from imbalanced data. In order to make good use of budgetary resources in informational campaigns about energy subsidies and so minimize public resource wastage and thereby provide accurate data on investment subsidies, public institutions are interested in identifying which organizations are potential beneficiaries. Consequently, correctly predicting which firms have applied for a financial subsidy is a desirable property of the classifier. Optimal deployment of this policy instrument thus depends on the direct interaction of policymaker and potential beneficiaries –represented by the minority class.

Taking this problem of imbalanced classification into account, many studies have pointed out that classification algorithms are extremely accurate for majority classes, but significantly less so for minority classes. The classification performance of standard classification algorithms is negatively affected by imbalanced datasets because minority cases cannot be identified, even though they are generally the most interesting (Barandela et al., 2003; Fernández et al., 2017; Haixiang et al., 2017; Krawczyk, 2016; Lopez et al., 2013). Researchers in the field of learning from imbalanced data have focused on using data sampling algorithms or external approaches (Aditsania et al., 2017; Brownlee, 2020; Chawla et al., 2002; Estabrooks et al., 2004; Garcia et al., 2012; Gosain & Sardana, 2017; He et al., 2008; Nimankar & Vora, 2021; Tallo & Musdholifah, 2018), modifying standard modelling algorithms or internal approaches (Lin & Chen, 2013; Vora & Iyer, 2018; Wang & Yao, 2009; Zong et al., 2013), combining both internal and external approaches or cost-sensitive learning techniques (Sun et al., 2007), and choosing appropriate performance metrics (Japkowicz & Stephen, 2002; Moniz et al., 2017; Saito & Rehmsmeier, 2015).

Since we focus on evaluating model performance, we split the dataset into a training dataset (70% of the sample) to fit the model and a test dataset to validate it on an unseen dataset (30% of the sample). In order to handle the imbalance issue, we balance the number of instances across the classes in the training dataset using a data sampling algorithm –rather than a modelling algorithm– which deals with class imbalance. Specifically, we choose the Synthetic Minority Oversampling Technique (SMOTE), proposed by Chawla et al. (2002) to balance the training dataset. SMOTE is an oversampling method whose key point is that it creates extra minority instances (synthetic instances) by interpolating between minority class instances which are within a neighborhood (Chawla et al., 2002). In fact, SMOTE is the most widely known data sampling method and is commonly used in practice to balance class distribution in the training dataset (García et al., 2016). Fernández et al. (2017) point out that the popularity of SMOTE stems from its simplicity in terms of the procedural design as well as its robustness when chosen to pre-process unbalanced data in many different applications.

Specifically, new minority instances are created as follows: for each minority instance, k neighbors are randomly selected; generally, the number of nearest neighbors used to generate new instances of the minority class is k=5. Depending on the amount of oversampling required, s neighbors from the k ones ($s \leq k$) are randomly chosen again. For example, for 300% oversampling, three neighbors from the k=5 are considered. The synthetic minority instances come from multiplying the difference between the minority instance and each of its neighbors (three out of the five in 300% oversampling is considered) by a random number between 0 and 1. In sum, SMOTE carries out an interpolation among neighboring minority class instances. As such, it increases the number of minority class instances by introducing new minority class examples in the neighborhood, thereby helping the classifiers to improve its generalization capacity and, hence, the performance of the classifiers on minority class instances. Figure 2 shows how synthetic minority instances are created.

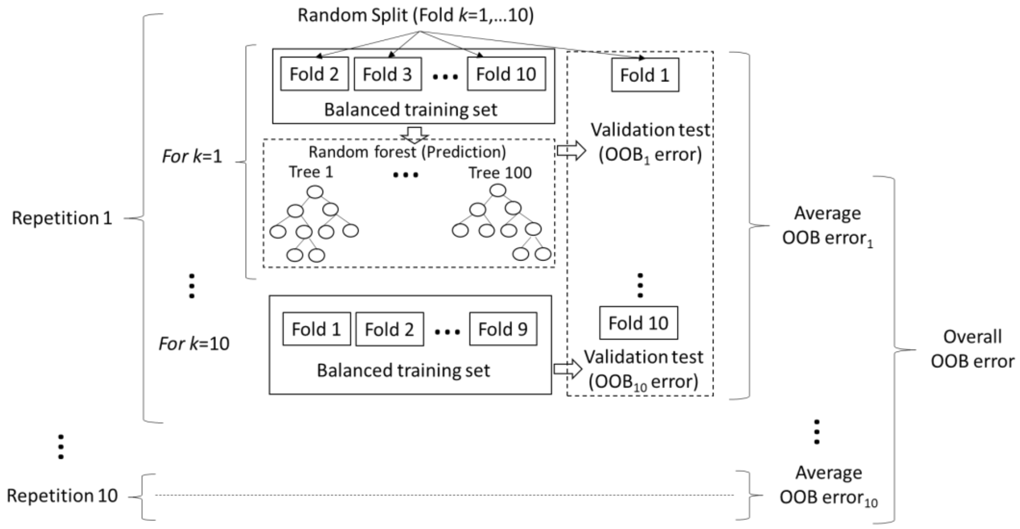
Figure 2. SMOTE method to create extra minority instances



Note: (1) X_0 is the minority instance; (2) X_1, X_2, X_3, X_4, and X_5 are the nearest neighbors; (3) X_1, X_2, and X_5 are the nearest neighbors randomly selected; (4) X_s is the synthetic minority instance from multiplying the difference between the neighbors randomly selected and the minority instance by a random number between 0 and 1 (black dots).

We then fit a random forest algorithm to the synthetic training set, which performs much better on the minority class since there are almost the same number of observations in the minority class as in the majority class. We build a random forest model with a repeated k-fold cross-validation algorithm. Specifically, we consider 10 repetitions and k=10 folds. For each repetition, the balanced training set is randomly split into 10 folds. Thus, there is a different split of the balanced training set in each repetition. Each fold is treated as a validation set or out-of-bag sample (OOB sample) to compute the performance score of a random forest model, while the remaining nine folds are used to train it. The number of trees we consider for training a random forest is 100. Given that we consider 10 repetitions –k=10 and 100 trees in each training set– the overall number of trees created is 10,000. The algorithm is summarized in Figure 3.

Figure 3. Random forest model with a repeated *k*-fold cross-validation algorithm



Note: repetitions are 10; *k*=10 folds, where nine folds are used for training and one is treated as a validation set or out-of-bag sample (OOB sample); balanced training set is randomly split into 10 folds; overall number of trees created is 10,000 (100 trees in each training set, *k*=10, and 10 repetitions); overall OOB error is the average of OOB errors in every repetition.

To create each tree, the random forest method selects several predictor variables, thereby preventing any one particular feature that may be highly influential from dominating many trees. Hence, each tree is split based on slightly different samples and different features, providing decorrelated trees and producing a more accurate predictor. Each tree's predictions are aggregated so as to obtain the final predictor. As *k*=10, a random forest model is training 10 times in each repetition. At each repetition, the estimated prediction error is computed as the average of the 10 prediction errors computed in each OOB sample. The above steps are thus repeated 10 times, and the overall prediction error (or overall OOB error) is the average of OOB errors in every repetition.

Moreover, we use the random forest model trained using the balanced training set to generate predictions on the test dataset, which is 30% of the dataset we set aside at the beginning of the procedure. To do this, we use the confusion matrix (illustrated in Table

4), which summarizes information about actual and predicted classification return by the classifier. Specifically, among the minority class instances (called the "positive class" in the table), those which the classifier correctly identifies as positive are called true positives (TP), whereas those wrongly identified as negative are false negatives (FN). The majority class instances (called "negative class" in the table) that are correctly identified are true negatives (TN) and, finally, those that are incorrectly predicted are false positives (FP). Among them, TP and TN are the correct predictions, while FP and FN are the incorrect predictions.

Table 4. Confusion matrix design

	Positive prediction	Negative prediction
Positive class	# TP	# FN
Negative class	# FP	# TN

Note: True positives (TP) and true negatives (TN) are the correct predictions. False positives (FP) and false negatives (FN) are the incorrect predictions.

Based on the information obtained from the confusion matrix, we assess the performance of the classifier with regard to the positive and negative classes in the test dataset, computing some widespread performance metrics, which are reported in Table 5. As regards these metrics: (i) the recall or sensitivity is the true positive rate (TPR); i.e., the fraction of true positives correctly picked up; (ii) the specificity or inverse recall is the true negative rate (TNR) and is used to know how many of the negatives are correctly picked up; (iii) informedness (Powers, 2011) combines recall and specificity into a single metric. This indicator ranges between -1 and 1, with 1 being reached in the event of perfect classification; (iv) positive predictive value (PPV) –also known as precision– is defined as the fraction of positively predicted instances that are truly positive: in other words, the ratio between true positives and all positives (true and false positives); (v) similarly, the negative predictive value (NPV) –also known as inverse precision– shows the relationship between true and false negatives; (vi) precision and inverse precision are combined into a single metric, ranged in the interval [-1,1] and called markedness (Powers, 2011); (vii) the F_1 measure (Zijdenbos et al., 1994) combines precision and recall into a single metric by computing their harmonic mean; and (viii) to overcome the drawbacks of previous metrics in the event of imbalanced datasets (overoptimistic inflated results), informedness and markedness are combined into a single metric by calculating their geometric mean. This last indicator refers to the Matthews correlation coefficient (MCC) (Baldi et al., 2000), which is an effective solution to overcome the class imbalance problem. MCC only produces a high truthful score if the classifier obtains good results in the four confusion matrix entries.

Table 5. Performance measures: metrics

Measures	Definition
Recall	$\frac{TP}{TP+FN}$
Specificity	$\frac{TN}{TN+FP}$
Informedness	$\frac{TP}{TP+FN}+\frac{TN}{TN+FP}-1$
Precision	$\frac{TP}{TP+FP}$
Inverse Precision	$\frac{TN}{TN+FN}$
Markedness	$\frac{TP}{TP+FP}+\frac{TN}{TN+FN}-1$
F_1	$\frac{2\cdot precision\cdot recall}{precision+recall}$
MCC	$\frac{TP\cdot TN-FP\cdot FN}{\sqrt{(TP+FN)\cdot(FP+TN)\cdot(TP+FP)\cdot(FN+TN)}}$

Note: TP equals true positives; TN equals true negatives; FP equals false positives; and FN equals false negatives.

Finally, we measure the variable importance in random forest modelling to select the most relevant explanatory variables for predicting the target variable. For this purpose, we use the permutation feature importance method, whose main idea is to calculate the importance of predictors by randomly permuting each of them in the training set and computing the reduction in the OOB prediction error. In particular, each predictor variable is shuffled in the training set and a prediction model with the shuffled dataset is implemented. The higher the reduction in predictive performance, the greater the influence the predictor has.

1.5. EMPIRICAL RESULTS

1.5.1. Application of a traditional approach

Prior to applying the random forest approach for unbalanced samples –and in order to test whether this approach has a greater predictive capacity than traditional models– we perform some logit regressions in this section. The dependent variable is still whether an SME has applied or not for a public investment subsidy (defined in Section 4.2). As regards the independent variables –and given the impossibility of including in the model all those described in Table 3– we choose three variables that the literature has mostly associated with requesting subsidies for energy efficiency (specifically, total indebtedness, non-current assets, and cash holdings).

Results are shown in Table 6, which contains two different panels: Panel A –showing the results related to the logistic regressions performed– and Panel B –showing the results regarding performance measures defined in Table 5. As regards Panel A, Regression (I) shows the results for the logit regression, where none of the three independent variables included are significant. For its part, Regression (II) shows the same logit regression but applying the SMOTE technique (i.e., balancing the sample, as previously explained in Section 3.3). The three independent variables are now statistically significant which, a priori, indicates better predictive capacity. Specifically, total indebtedness is negatively related to the probability of requesting an energy efficiency subsidy, while non-current assets and cash flows have a significantly positive impact. In addition –and after checking the results of performance measures in Panel B– we see how the predictive power is also greater in Regression (II), i.e., the predictive power increases when the SMOTE sample balancing technique is applied in a logit regression. These results allow us to conclude that applying the SMOTE technique implies an improvement in the predictive capacity of the logistic model. This is because none of the three independent variables commonly associated with requesting subsidies for energy efficiency are statistically significant when the original unbalanced sample is considered. By contrast, when the artificially balanced sample is used, the three become relevant in terms of explaining the probability of requesting an energy efficiency subsidy.

In any case, in these logit models (including the SMOTE logit) we have had to previously select the set of variables that impact the probability of an SME requesting a public investment subsidy. However –and as discussed above– such selection is extremely difficult. An alternative is therefore the random forest approach which –based on a much larger set of predictors– allows us to determine which of these have the greatest impact on our dependent variable of interest.

Table 6. Logit regression results

Panel A. Logit regressions		
Variables	(I) Logit regression	(II) SMOTE logit regression
Total indebtedness	-0.693	-0.835***
Non-current assets	4.903	18.909***
Cash holdings	0.000	0.000**
Intercept	-2.719***	0.442***
AIC	499.57	3625.3
Chi-square (p-value)	0.338	0.000
Optimal cut-off	0.0350	0.559

Panel B. Performance measures		
Metrics	Logit	SMOTE Logit
Recall	0.923	0.230
Specificity	0.188	0.868
Informedness	0.111	0.099
Precision	0.025	0.037
Inverse Precision	0.991	0.981
Markedness	0.016	0.018
F_1	0.048	0.064
MCC	0.041	0.042

Note: total indebtedness is measured as the ratio of total debt over total equity and debt; non-current assets are measured as the ratio of investment property over non-current assets; and cash holdings are defined as the ratio of cash and cash equivalents over total assets.

1.5.2. Results of applying the random forest approach for an unbalanced sample context

As mentioned above, we face a problem with our unbalanced sample since the class distribution (majority versus minority class) is severely skewed. Specifically, there are 1,919 firms in the majority class instances and only 73 in the minority class. Thus, the imbalance ratio is equal to 0.03804, which is approximately a 1:27 class ratio. This unequal distribution of classes in the dataset affects the efficient channeling and use of this public money. Optimal deployment of public policies depends on the direct interaction of policymaker and potential business beneficiaries of public investment subsidies, represented by the minority class.

After splitting the dataset into a training dataset (70% of the sample) and an unseen dataset (30% of the sample), the training set consists of information related to 1,396 firms, while the number of observations of the test dataset is 596 firms. In the training set, there are 1,344 majority class instances and 52 minority class instances, and in the test set, 575 and 21 observations, respectively. Consequently, both sets have a similar distribution. In the training set, 96.27% of the observations correspond to firms who do not receive a subsidy and 3.73% to firms who do. The test set consists of 96.47% of firms who do not receive a subsidy and 3.53% of firms who do. The same level of imbalance is therefore maintained (0.03804 imbalance ratio).

Once our training set has been transformed –applying the SMOTE technique to balance the sample by creating new minority instances as stated in Section 3.3– the class distribution of the synthetic training set is balanced, with 1,344 observations in the majority class and 1,300 (original and synthetic) observations in the minority class, as a result of duplicating the size of the minority class 24 times. In other words, since the size of the minority class in the training set is equal to 52, 24*52=1,248 synthetic observations are generated and the final size of the minority class of the training set is (24*52)+52=1,300. The overall prediction error (or overall OOB error) shows a value of 0.417%, such that the balanced training set model accuracy is around 99.583%.

The confusion matrix results are illustrated in Table 7. As regards the minority (or positive) class, we see how the classifier correctly classifies all firms, such that the model is able to identify 100% of the firms that would be interested in receiving an energy subsidy. With regard to the majority (or negative) class, the classifier incorrectly classifies one firm as positive, while 574 firms are correctly classified as negatives. Given our testing set, the set of potential beneficiaries is reduced from 596 firms to 22, without any false negatives and with just one false positive in the set.

Table 7. Confusion matrix results

	Positive prediction	Negative prediction
Positive class	21	0
Negative class	1	574

Note: True positives (TP) and true negatives (TN) are the correct predictions. False positives (FP) and false negatives (FN) are the incorrect predictions.

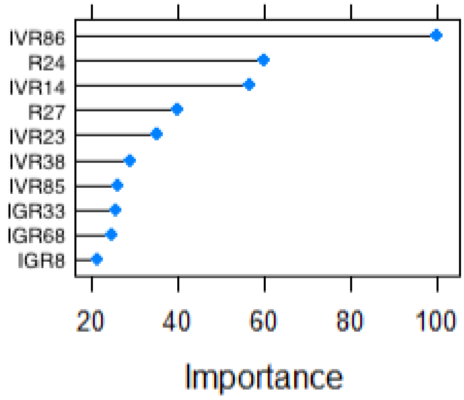
The scores related to the performance metrics are reported in Table 8. Specifically, this table shows: (i) as regards recall or sensitivity, it can be seen that the classifier achieves one in the true positive rate (TPR), which means that the model is able to identify 100% of the firms that would be interested in receiving an energy subsidy; (ii) as regards the specificity or inverse recall, the model detects 99.8% of the firms that would not be interested in receiving an energy subsidy; (iii) informedness is 0.998 –very close to 1– which means both high TPR and high TNR; (iv) as regards precision, the model is very accurate, since only 4.5% of the firms detected as potential beneficiaries are in fact not; (v) inverse precision is equal to 1, which means that true negatives correspond to all negatives (true and false negatives); (vi) for its part, markedness shows a high value –close to the best possible value– meaning that both PPV and NPV are high; (vii) F_1 also shows a high value, equal to 0.977 in the [0,1] interval, which could be interpreted as the model generating excellent predictions; and (viii) the MCC value is equal to 0.976 in the [-1,1] interval –very close to the best value. This reflects the high predictive capacity of the model.

Table 8. Performance measures: scores

Measures	Score
Recall	1.000
Specificity	0.998
Informedness	0.998
Precision	0.955
Inverse Precision	1.000
Markedness	0.954
F_1	0.977
MCC	0.976

Finally, Figure 4 shows the variables ranked as being more important than the others. The most useful predictors for predicting which SMEs are potential energy beneficiaries are related to liquidity and indebtedness. The predictor in the first position of the ranking is denoted by **IVR86** (liquidity), which captures the increase in investment capacity measured in relation to the average of the sector (and defined as short-term financial assets divided by net sales). For their part, **R24**, **IVR14**, **R27** and **IVR23** are related to indebtedness. The variable **R24** represents the financial debt maturity structure of a firm (calculated as short-term financial debt over long-term financial debt); **IVR14** captures the percentage of long-term-debt (maturity of over one year) which is nonfinancial (other types of debt not associated with bank loans) measured in relation to the average of the sector; **R27** captures a firm’s interest and related charges on financial debt, which are requested from banks or financial institutions; and **IVR23** is the variation ratio of a firm’s debt maturity structure measured in relation to the average of the sector.

Figure 4. Variables ranked as most important



Note: **IVR86** refers to an industry variation rate of R86 (Short-term financial assets/Net sales); **R24** equals Short-term financial debt/Long-term financial debt; **IVR14** refers to an industry variation rate of R14 (Long-term non-financial debt/Long-term debt); **R27** equals Financial expenses/Financial debt; **IVR23** refers to an industry variation rate of R23 (Short-term debt/Long-term debt); **IVR38** refers to an industry variation rate of R38 (Non-current financial assets/Non-current assets); **IVR85** refers to an industry variation rate of R85 (Short-term financial assets/Short-term debt); **IGR33** refers to an industry growth rate of R33 (Financial incomes-Financial expenses)/Earnings before interest and taxes); **IGR68** refers to an industry growth rate of R68 (Current assets-inventories-trade receivables)/Short-term debt); and **IGR8** refers to an industry growth rate of R8 (Long-term financial debt/Long-term debt).

1.5.3. Traditional versus random forest approaches for unbalanced samples

Table 9 shows the comparison of performance measures between the random forest approach for unbalanced samples and traditional approaches. After verifying the changes experienced therein, we see how the increase in performance measures is very pronounced (specifically, with regard to informedness, precision, markedness, and F_1). This comparison reflects the greater potential of using the random forest model within this context, which makes it a suitable and accurate approach for determining which predictors affect the probability of SMEs requesting a public investment subsidy.

Table 9. Performance measures: comparisons

Measures	Random forest *versus* Logit	Random forest *versus* SMOTE logit
Recall	0.077	0.77
Specificity	0.81	0.13
Informedness	0.887	0.899
Precision	0.93	0.918
Inverse Precision	0.009	0.019
Markedness	0.938	0.936
F_1	0.929	0.913
MCC	0.935	0.934

1.6. DISCUSSION OF THE MAIN FINDINGS

Applying a sophisticated random forest approach for unbalanced samples, this chapter identifies the profile of which SMEs display the greatest potential to invest in energy efficiency measures so that governments can direct their efforts towards them, and thereby enhance the effectiveness of public policy allocation and execution. Based on this, several findings and contributions to previous literature may be highlighted and discussed, and which directly aim to cover the gaps identified. Firstly, this research provides a specific profile of which industrial SMEs are potential beneficiaries for investment in efficiency energy measures. More specifically, this profile shows the SMEs which – beyond merely meeting the legal requirements– are more likely to apply for this public aid and then make investments in energy efficiency. We find that, in general terms, aspects related to business liquidity and indebtedness are the main drivers that make SMEs in the industrial sector finally decide to apply for these public subsidies. This evidence places special emphasis on the importance of good economic-financial health, which is vital for SMEs vis-à-vis investing in energy efficiency measures, given that lack of liquidity or excessive indebtedness prevents them from undertaking projects (which chiefly affects investments in efficient energy).

Secondly, in order to predict an accurate profile it has been necessary to implement more sophisticated techniques. In fact, this research evidences the greater predictive capacity of using the random forest approach for unbalanced samples compared to traditional ones. Specifically, two key methodological challenges in this field have been addressed. On the one hand, the random forest approach (Breiman, 2001, 2004) allows an accurate SME profile to be defined by handling a high volume of predictor variables and by creating several independent decision trees. This large volume of indicators (in this case, 528 indicators for each company, which implies over a million observations) does not allow the application of logistic regression or discriminant analysis models in which the number of parameters would eliminate the degrees of freedom of the model. Moreover, our results allow us to affirm that applying traditional models in this field would not provide accurate results due to said models' lower predictive capacity. Added to this is the fact that the traditional model would demand prior selection of the explanatory variables, which is extremely complicated. On the other hand, a further issue is that samples in this field are fairly unbalanced (such that the proportion of SMEs who applied and who are potential energy beneficiaries is very small, even though this is the group of greatest interest to public institutions). If this lack of balance is not considered by researchers, the results obtained would be biased because the "minority class" would not really be considered in the estimation. To address this issue, sample balancing techniques are applied in this chapter, thereby increasing the accuracy of both the estimation and the identification of SME profile.

The choice of the random forest model for this work is due to its innumerable advantages. On the one hand, random forest overcomes the over-fitting problem of decision trees, evidences good tolerance to noise and anomaly values, and exhibits good scalability and parallelism to the problem of high-dimensional data classification (Boinee et al., 2005; Breiman, 2001; Liaw & Wiener, 2002). In addition, random forest is a non-parametric classification method and is data-driven. It trains classification rules by learning given samples and it does not require prior classification knowledge. Moreover, this approach is faster than boosting, is simple, and is relatively quick to develop and can be easily parallelized (Breiman, 2001). In addition, it gives useful internal estimates of error, strength, correlation, and variable importance. Apart from taking into consideration these advantages, we chose random forest as the classifier because numerous articles for imbalanced data classification over the years have combined data resampling (in particular, SMOTE) and random forest in order to achieve classification goals. The balanced samples for training generated by SMOTE improve the performance of classifiers. They are used to train a random forest model to recognize the rate of samples in the minority class (e.g., Ma & Fan, 2017; Sholihah & Hermawan, 2023; Wu et al., 2022; Xu et al., 2020). Finally, we highlight that we have not compared the classification performance of random forest with other ensemble algorithms because of the extraordinary performance of random forest. In particular, the F-value index and MCC index used to evaluate the classification performance for the imbalanced dataset are equal to 0.977 and 0.976, respectively, as shown in Table 8.

Thirdly, identifying the profile of potential beneficiary SMEs helps governments to directly filter which SMEs might be possible beneficiaries, thereby reducing the costs (in particular, dissemination and information costs) that would be incurred by not having this profile, in addition to increasing the effectiveness of public aid allocation. Based on our evidence, public bodies should be aware of the need to specifically target their calls towards companies who are more likely to invest in energy efficiency measures. Should governments fail to pay attention to this profile and launch more generalist calls, the channeling of public subsidies becomes more difficult, which often results in a lower investment rate in energy efficiency. Beyond what are merely economic motivations, success in the design and implementation of public calls is also important in terms of boosting the commitment to sustainability, given the environmental advantages to be derived from energy efficiency measures (Hrovatin et al., 2021). Similar to what happens in commercial building operations, investment subsidies play a crucial role in connecting the broader goal of carbon reduction through practical, actionable steps (Li et al., 2022). The financial support provided by subsidies facilitates the implementation of energy-efficient technologies, thus contributing to a more sustainable and environmentally friendly approach to commercial building management.

Fourthly, although this research is focused on the specific context of the Region of Murcia, our findings can be generalized both at the country and sector level. At the country level, Spain displays a similar energy consumption across its various regions –in terms of distribution of sources– with electrical energy representing the highest cost (Spanish National Statistics Institute, 2019). For this reason, Spain tends to show a strong commitment to producing electrical energy from cleaner and more efficient sources (Red Eléctrica, 2022), highlighting the relevance of investing in energy efficiency measures. Added to this is the fact that the European Union has recently agreed to end coal and gas heating by 2040, which represents an added boost at country level in terms of promoting more energy efficiency measures (González, 2023). Going further, the Region of Murcia –with its distinctive Mediterranean climate and specific combination of socioeconomic factors– provides a representative case that resembles other European regions. This means that the results obtained here can be extrapolated to those regions which display similar features. At the sector level, the findings obtained can be generalizable to organizations that operate in the industrial sector (or similar sectors), which is where public aid has been analyzed in this article, and which represent a high proportion of both the regional and national product fabric.

Finally, this study has some limitations that may lead to future research lines. First, this study is focused on public subsidies as the main driver of investments in energy efficiency measures. Future studies may consider other drivers that alleviate other barriers (both economic and otherwise) that make it difficult for SMEs to invest in efficient energy. Secondly, this study is focused on SMEs from the Region of Murcia. Future studies could analyze to what extent the profile stated in this chapter is the same for larger companies and for companies that operate in other contexts whose (political, fiscal, economic, and social) features differ slightly from those of Spain. Thirdly, future papers may delve into which specific aspects of liquidity and indebtedness within an enterprise would be valuable, thereby providing a more specific profile of SMEs that could potentially benefit from public investment subsidies. Finally, it would be interesting to explore to what extent those businesses who are potential beneficiaries of these public subsidies ultimately do actually request them and invest in said support to achieve energy improvements in their organizations. To do this, it may be useful to examine the motivations, implications, and impact that such public subsidies have on organizations.

1.7. CONCLUDING REMARKS

Implementing efficient energy measures should not only be encouraged for environmental reasons but also because of the benefits in terms of business competitiveness (Hrovatin et al., 2021), increased cost saving, and performance. Despite these motivations, many companies (especially SMEs) are still failing to implement energy efficiency measures (Cagno et al., 2017; Kostka et al., 2013) due to the barriers that prevent them from undertaking these investments (Thollander et al., 2013). In an effort to counteract these barriers, public institutions often define and implement public programs that seek to boost the attractiveness and appeal of investments in energy efficiency measures (Prasad Painuly, 2009). Specifically, public investment subsidies are one of the most prominent instruments to counter these economic-financial barriers and so encourage companies to make such investments (Brunke et al., 2014; Cagno et al., 2015; de Groot et al., 2001; Fleiter et al., 2012). Bearing this in mind, this chapter seeks to identify the profile of which SMEs display the greatest potential to invest in energy efficiency measures so that governments can direct their efforts towards such SMEs and thereby enhance the effective allocation and execution of these public policies. Based on a sample of 1,992 SMEs from the Region of Murcia (Spain) over the period 2013-2018, this chapter uses a random forest approach and techniques for unbalanced samples to identify SME profile. Results show that the most useful predictors for predicting which SMEs in the industrial sector are potential energy beneficiaries are those related to liquidity and indebtedness.

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APPENDIX A. Energy consumption based on the NACE Rev 2 classification (2019)

NACE Rev 2 Codes		Electricity	Gas	Diesel	Fuel oil	Coal and coke	Biofuels	Heat and other energy	Total energy consumption
07	Mining of metal ores	44,697	639	5,504	674	4,920	0	447	56,881
08	Other mining and quarrying	73,906	28,482	65,699	2,989	0	0	436	175,998
10	Manufacture of food products	1,073,429	509,278	188,791	9,344	781	13,569	15,631	1,828,614
11	Manufacture of beverages	133,368	57,609	28,180	25,025	0	2,203	25	249,320
13	Manufacture of textiles	101,661	52,398	5,556	48	0	282	149	160,623
14	Manufacture of wearing apparel	13,978	1,656	2,825	18	0	0	40	18,594
15	Manufacture of leather and related products	21,160	6,391	3,087	272	0	0	0	31,296
16	Manufacture of wood and of products of wood and cork	133,321	10,535	27,533	1,013	0	4,101	559	177,762
17	Manufacture of paper and paper products	399,019	231,197	13,576	14,389	0	4,854	16,216	681,805
18	Printing and reproduction of recorded media	66,381	11,069	6,120	0	0	0	46	84,221
19	Manufacture of coke and refined petroleum products	280,493	452,498	305	0	0	0	113,275	846,631
20	Manufacture of chemicals and chemical products	720,192	589,242	31,076	4,280	7	3,108	194,772	1,581,572
21	Manufacture of basic pharmaceutical products and pharmaceutical preparations	115,367	41,979	3,760	5,604	0	0	1,541	169,302
22	Manufacture of rubber and plastic products	424,717	48,921	22,289	3,798	0	214	18,666	519,741
23	Manufacture of other non-metallic mineral products	566,444	626,376	89,815	14,525	87,924	15,581	11,387	1,416,290
24	Manufacture of basic metals	1,113,460	441,515	14,311	11,061	10,974	7	78,333	1,672,215
25	Manufacture of fabricated metal products, except machinery and equipment	307,052	98,754	50,213	2,836	24	393	5,428	472,333
26	Manufacture of computer, electronic and optical products	24,258	2,043	2,122	131	0	4	173	29,101
27	Manufacture of electrical equipment	120,849	17,188	7,625	365	0	0	1,501	148,699

28	Manufacture of machinery and equipment	90,919	17,785	23,241	515	0	51	463	135,998
29	Manufacture of motor vehicles, trailers, and semi-trailers	372,113	100,795	23,025	1,692	0	246	714	501,278
30	Manufacture of other transport equipment	69,192	14,739	12,639	0	0	1	966	100,504
31	Manufacture of furniture	38,619	3,442	17,640	50	0	111	26	60,048
32	Other manufacturing	22,495	2,510	2,312	0	0	0	101	27,761
33	Repair and installation of machinery and equipment	23,719	4,273	24,560	109	0	0	91	55,426
	Total	6,350,809	3,371,314	671,804	98,738	104,630	44,725	460,986	11,202,013

Note: The figures are expressed in thousands of euros. Some NACE Rev 2 codes that are part of this study are not included in this table because they do not report data.

Source: Spanish National Statistics Institute.

CHAPTER 2

IMPACT OF PUBLIC GUARANTEES ON OPTIMAL DEBT LEVELS FOLLOWING THE COVID-19 PANDEMIC: EFFICIENCY IN THEIR ALLOCATION

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ABSTRACT

The COVID-19 pandemic triggered a sudden drop in companies' sales and turnover, which resulted in serious liquidity and solvency problems. In an effort to cushion these unfavorable effects, a credit guarantee plan was launched in 2020 by the Spanish Government to mitigate the effects of COVID-19 by injecting firms with liquidity. This chapter seeks to analyze the impact of this public policy on SMEs' optimal debt levels and to examine whether the allocation of this public funding has been efficiently targeted at those SMEs suffering temporary distress as a result of the pandemic. Based on a sample of 3,305 Spanish SMEs, our results show that the government's interventionist policy swelled excess debt levels –mainly due to the increase in excess long-term debt– and deviated them from the optimum. Moreover, although these public guarantees should mostly have been aimed at SMEs experiencing a temporary decline due to COVID-19, we find that these SMEs were the least likely to receive liquidity injections.

2.1. INTRODUCTION

The pandemic caused by COVID-19 triggered a crisis that impacted health, social, and economic areas worldwide. In terms of the economic effects, this health crisis hit financial markets as well as the activity and performance of most companies, whose sales and profits plummeted, resulting in liquidity and solvency problems (Almeida, 2021; Blanco et al., 2021; Demmou et al., 2021; He et al., 2020). In an effort to cushion these unfavorable effects, governments worldwide implemented several policies to reverse this delicate situation (Kahn & Wagner, 2021). Added to these were the measures launched by other institutions such as the Spanish Mutual Guarantee Societies, who also helped to mitigate the economic problems arising from the COVID-19 pandemic (Corredera-Catalán et al., 2021). Prominent among the various measures implemented to alleviate the negative effects of the pandemic were public guarantees –whose objective was to facilitate company access to credit (Core & De Marco, 2021). These public guarantees – often channeled through banking entities– involve governments reimbursing the banking entity for the amount of the outstanding loan should the firm default (Corredera-Catalán et al., 2021).

In Spain, the Official Credit Institute (ICO)[1] helped to mitigate the effects of the COVID-19 crisis both by facilitating liquidity and/or by encouraging company investment (Blanco et al., 2021). Specifically, a public credit guarantee plan –endowed with over €100,000 million– was launched in 2020 to cover new loans and other forms of financing in addition to renewing the support granted by financial entities to companies and self-employed persons to meet their financing needs (ICO, 2020; *Real Decreto-Ley 25/2020, de 3 de julio, de medidas urgentes para apoyar la reactivación económica y el empleo*, 2020). Despite this public aid being led by the ICO, management thereof was conducted through the banking sector, specifically by the financial entities that voluntarily joined this program.

Although any company or self-employed worker domiciled in Spain who suffered financial hardship due to COVID-19 was eligible to become a beneficiary of this aid, the distribution agreed by the government meant that small and medium-sized enterprises (SMEs) and the self-employed were the main recipients (ICO, 2020). Over 55% of SMEs in Spain requested financing lines after the outbreak of the pandemic, and several operations were guaranteed amounting to €64,120.8 million by the end of 2020. This

[1] The Official Credit Institute (ICO) is a Spanish national bank linked to the Secretary of State for Economy and Business Support. It plays a three-fold role as a credit institution, an economic policy financial instrument, and as a state funding agency. For more information, visit the website: https://www.ico.es.

allowed SMEs to receive €90,221.9 million of financing to guarantee their liquidity (ICO, 2020). The government's interventionist policy may have impacted debt levels since this aid –which involves injecting liquidity into companies– may have increased SMEs' abnormal level of debt (by raising debt levels above optimal levels), beyond transforming said organizations' capital structure (by replacing short-term guarantees with banks for long-term public guarantees with a period of grace, a feature of this public aid for containing COVID-19). Added to this is the fact that the banks –responsible for managing and channeling these "public" guarantees– may have adopted more risky or imprudent decisions (compared to those they would otherwise take when granting private bank guarantees) since the risks and costs they assume are much lower (Cordella et al., 2018; Gropp et al., 2014; Leonello, 2018). All of this led to inefficient allocation of public guarantees that generated excess liquidity in SMEs, and increased debt levels above the optimum.

In addition to adequately designing and implementing public policies, it is vital to analyze to what extent public funding has been distributed efficiently and in accordance with the objective established by the financier. In this sense, public credit guarantees –promoted by the Spanish government– were intended to inject liquidity into companies who experienced a significant decline in turnover and sales, caused exclusively by the COVID-19 pandemic (ICO, 2020). For this reason, efficient allocation of this public aid is conditional upon it being directed towards SMEs who suffer temporary economic-financial distress, i.e., towards SMEs who, after the outbreak of the COVID-19 pandemic, were at increased risk of default and/or of seeing their growth opportunities, non-debt tax shield, or financial performance negatively impacted (e.g., Abu Hatab et al., 2021; Apergis et al., 2022; Gormsen & Koijen, 2020; Padhan & Prabheesh, 2021; Sarker et al., 2022; Sun et al., 2022). Moreover, SMEs who suffered any distress prior to COVID-19 (i.e., distress considered to be structural) should not have been beneficiaries of this public aid. This is because if this public liquidity is directed towards SMEs that suffer structural distress and which are close to bankruptcy then these SMEs would tend to invest this money in very risky projects (even those with a below zero NPV), thereby increasing the shareholder-creditor agency conflict (Ayotte et al., 2013; Chu, 2017) and reducing efficient allocation of this public aid.

Based on this, the present chapter pursues a twofold objective. First, we analyze in Spanish SMEs whether, as a consequence of the Spanish government's interventionist policy, there were changes in excess debt levels in 2020 due to the COVID-19 pandemic by comparing actual (observed) debt levels and optimal debt levels. This allows us to check how debt targets may deviate from optimal thresholds when excess liquidity is injected by governments. Second, we analyze whether or not the allocation of public funding (mainly channeled through guarantees granted by the ICO) proved to be efficient by verifying to what degree this public aid has actually been directed towards SMEs that suffered temporary distress. Taking into consideration that this public aid was exclusively intended to remedy SMEs' "short-term" or "temporary" financial decline triggered by the health crisis, we test whether the potential distress suffered by an SME is structural (i.e., whether it was already present before the outbreak of the pandemic) or temporary (i.e., related to the outbreak of COVID-19). We also examine whether SMEs, as a result of this public aid, replaced bank guarantees (generally short-term) for public guarantees. This allows us to assess whether public aid has been used efficiently for the real purpose intended by the government (i.e., to remedy temporary distress) or whether, by contrast, there is inefficiency in the allocation of this aid.

Our results show that this government's interventionist policy swelled excess debt levels –mainly due to the increase in excess long-term debt– and deviated them from the optimum. Moreover, although these public guarantees should mostly have been aimed at SMEs experiencing a temporary decline due to COVID-19, we find that these SMEs were the least likely to receive liquidity injections.

By addressing these objectives, this chapter seeks to contribute to the literature in the following main ways. Firstly, this chapter contributes by providing novel and fresh evidence on pattern changes experienced in leverage due to the Spanish government's intervention. The injection of liquidity has caused a deep structural change by replacing short-term with long-term debt under favorable conditions by SMEs. This fact, which is particularly important, should be taken into account by researchers, and should alert them to consider this COVID period when carrying out new studies, due to the abnormal patterns experienced by several economic-financial indicators (such as liquidity and debt ratios). Secondly, this research provides evidence on the effectiveness of the channel used by the Spanish government to target government funds, by using banking entities as intermediaries to deploy these public guarantees (rather than opting for direct government allocation) –taking the problems associated with information asymmetries, moral hazard, and/or adverse selection into account. Finally, this research also helps policymakers to adopt decisions about whether or not to make (disproportionate) injections of liquidity into the economy due to the impact this has on levels of optimal and excess debt. Particularly highlighted is the need to monitor the intermediation of public financing lines aimed at meeting the ultimate objectives set out in the calls (i.e., ensuring that the allocation of public aid is carried out efficiently).

This article is structured as follows. After this introduction, the second section reviews the literature on public guarantees and their allocation, and then proposes several research questions regarding these topics. The main methodological issues (i.e., sample, data, period, models, analysis) are then provided in the third section. The main results of this research are then highlighted in the fourth section. Finally, in the last section, the main conclusions obtained are stated and the key practical and theoretical implications are discussed.

2.2. LITERATURE REVIEW

2.2.1. Impact of the Spanish government's interventionist policy on debt levels

A company's ability to generate "cash" is key to its survival, particularly during a period of recession such as the one following COVID-19 (Belghitar et al., 2022). In the field of SMEs, this liquidity is even more important given the low level of cash these companies hold compared to large companies (Belghitar et al., 2022; Belghitar & Khan, 2013), to which is added the difficulty SMEs have in accessing the capital market. However, the COVID-19 pandemic triggered serious liquidity problems, arising from a sudden drop in sales and turnover, and which impacted businesses' normal functioning and operating (Cressy, 2006; Ghosal & Ye, 2015) –as Fairlie & Fossen (2022) also noted in the context of COVID-19. In addition, this liquidity crisis placed companies in a situation of particular vulnerability and increased the chances of bankruptcy and failure (Lu et al., 2020). This difficult situation forced policymakers worldwide to face the challenge of finding the most effective way to deploy government funds to cushion the negative effects of COVID-19 and thereby (at least partially) limit the downturn in the economy (Core & De Marco, 2021).

In this context, governments could opt for two different alternatives (Core & De Marco, 2021): they could grant public loans directly or could channel public guarantees through banking entities. In Spain, the government opted for the second option and engaged in a program of public guarantees –led by the ICO and managed by banking entities– and which was aimed at increasing company liquidity (ICO, 2020) and so offsetting the potential risks of insolvency arising from the sudden drop in turnover and sales caused by COVID-19. Channeling these public guarantees through banking entities made it possible to overcome several deficiencies that previous literature has associated with cases of direct government allocation, such as avoiding inefficiencies derived from political connections (Khwaja & Mian, 2005) and minimizing the costs derived from asymmetric information, since any financial losses suffered by the bank –as the lender– are potentially removed (Carvalho, 2014; Sapienza, 2004; Zecchini & Ventura, 2009). In addition, "public contribution" to the guarantee system usually implies a significant leverage effect since small cash outlays may leverage a large number and volume of loans (Corredera-Catalán et al., 2021). This makes public guarantees a "cost-effective way for the government to support bank lending to SMEs, because they require low initial outlays compared to direct lending" (Core & De Marco, 2021, p. 4).

These public guarantees are thus an interesting tool to improve access to credit for SMEs, who often experience greater difficulty in participating in private credit markets due to existing information asymmetries (Corredera-Catalán et al., 2021). Although these guarantees have contributed positively to strengthening SME stability, a large injection of liquidity, as was the case of Spain, may affect optimal debt levels –defined as the debt level that would result after considering the specific impact of its determining factors (e.g., Aybar-Arias et al., 2012; D'Amato, 2020; Lopez-Gracia & Mestre-Barbera, 2011; Lopez-Gracia & Sogorb-Mira, 2008; Serrasqueiro et al., 2012)– in particular with regard to long-term debt, which is the time horizon that characterizes such guarantees (ICO, 2020). The literature assessing public credit guarantee plans is clear in pointing out that these guarantees tend to increase debt levels (Gazaniol & Lê, 2021). This requires particular analysis, since excessive growth of SME debt levels –away from optimal thresholds– can lead to severe risk of default. Furthermore, a disproportionate increase in debt levels leads to greater financial instability, should the beneficiaries of these guarantees be unable to meet the commitments undertaken (Gropp et al., 2014).

In sum, we expect the interventionist policy implemented by the Spanish government due to COVID-19 –and which consists of promoting public guarantees to inject liquidity into businesses– to have increased excess debt levels (or abnormal debt levels) of Spanish SMEs in 2020 compared to pre-pandemic years. This is the question which we seek to find an answer to.

2.2.2. Efficiency in the allocation of public guarantees

Policies implemented by the Spanish government –in particular the public guarantees policy led by the ICO (ICO, 2020)– helped to alleviate the negative economic effects arising from the COVID-19 pandemic. However, efficient execution of these policies is complex –a challenge which is even greater in the field of SMEs since these organizations are highly decentralized and there is asymmetric information that increases the gap between SMEs' needs and government actions (Sun et al., 2022; Zhu et al., 2020). Added to this is the problem of "adverse selection" (Core & De Marco, 2021), which could lead to inefficient channeling of this public aid –i.e., when these public guarantees are channeled towards SMEs that do not suffer deterioration, towards SMEs that could have obtained private financing through other ways, or towards marginally risky SMEs that do not meet aid requirements.

The Spanish government's interventionist policy might have been considered efficient if the injection of liquidity had been directed towards SMEs who suffered temporary distress, as stated in the call for these grants (ICO, 2020). Here, it is necessary to differentiate between *structural distress* and *temporary distress*. We consider structural distress to be that which already existed before the outbreak of the pandemic, while temporary distress is a period of weak growth resulting from a specific event (such as the COVID-19 pandemic), where this cyclical shock is expected to return to its previous level shortly (Baily et al., 2001). Spanish government programs designed to contain the downturn in the economy were aimed exclusively at remedying temporary distress (ICO, 2020). In other words, beyond merely targeting SMEs that suffered any kind of decline, efficient allocation of this public aid should therefore have been aimed at firms whose downswings were temporary (i.e., distress resulting from the outbreak of the pandemic).

Efficient allocation of this public aid is thus conditional upon these guarantees being predominantly directed towards SMEs whose default risk, growth opportunities, NDTS, and/or financial performance worsened due to COVID-19, since these are the main economic-financial factors impacted by the pandemic (e.g., Abu Hatab et al., 2021; Apergis et al., 2022; Gormsen & Koijen, 2020; Padhan & Prabheesh, 2021; Sarker et al., 2022; Sun et al., 2022). More specifically, *default risk* and *business opportunities* are two factors affected by crises such as the one triggered by COVID-19 since, during economic downturns, firms are more constrained, growth opportunities become limited, and earnings volatility increases (D'Amato, 2020). In this sense, the pandemic increased firms' risk default (Apergis et al., 2022) beyond increasing the risk suffered by the banking sector (Elnahass et al., 2021). When analyzing a sample of Egyptian SMEs, Abu Hatab et al. (2021) state that the risks associated with COVID-19 are considered an unprecedented situation that posed significant risks and generated high levels of uncertainty. This makes default risk one of the variables that government interventionist policies seek to influence in order to contain the downturn in the economy. Moreover, SMEs' growth opportunities were also affected as a result of the COVID-19 pandemic (Gormsen & Koijen, 2020) since these businesses experienced a sudden drop in their revenues and an increase in their pressure on earnings. This is especially worrying in the case of SMEs, since one of the main barriers they face is, precisely, financing (Wang, 2016) –one of the aspects most severely impacted by COVID-19.

Additionally, *NDTS* might have represented the main alternative to reducing tax burdens for two main reasons: first, because SMEs are more likely to use NDTS instead of debt as a tax shield due to their lower probability rates, and second because SMEs often receive favorable treatment by the tax code (D'Amato, 2020; Lopez-Gracia & Sogorb-Mira, 2008). However, the onset of COVID-19 acted as a brake to using NDTS as an alternative to debt. Finally, SMEs' *financial performance* is another of the factors most severely affected by the distress these organizations experienced after the outbreak of the pandemic (Padhan & Prabheesh, 2021; Sun et al., 2022). Uncertainty is one of the main reasons undermining firm performance –and the recent COVID-19 pandemic resulted in considerable uncertainty in the global economy (Zhang & Zheng, 2022). SMEs suffered a drop of over 40% in their production volume compared to the year before the pandemic (Sarker et al., 2022). Added to this are other difficulties such as the postponement of the resumption of work, the slump in market demand, and restrictions on logistics and flow of people (Sun et al., 2022).

In this context, the role played by banking entities is vital in terms of achieving efficient allocation since the latter are responsible for allocating these "public" guarantees. Leaving the channeling of this public aid in the hands of the banks tends to minimize problems linked to direct government allocation, as discussed above (see Carvalho, 2014; Khwaja & Mian, 2005; Sapienza, 2004; Zecchini & Ventura, 2009). However, banks might have fewer incentives to screen and monitor borrowers in the presence of moral hazard. They may therefore tend to display more reckless behavior, since they become less concerned about assuming risks, given that they do not have to bear the costs of potential failure (Cordella et al., 2018; Gropp et al., 2014; Leonello, 2018). In other words, these public guarantees may induce banks to take excessive risks (e.g., allocating guarantees to firms that do not need extra liquidity or over-allocating them towards certain SMEs) (Gropp et al., 2014). In this way, future defaults might increase, leading to “a high cost of the scheme for public finances ex-post” (Core & De Marco, 2021, p. 7).

In sum, whether public credit guarantees were or were not directed towards SMEs suffering temporary deterioration is ultimately an empirical question, and is one which we attempt to find an answer to.

2.3. METHODOLOGY

2.3.1. Sample and data

Our sample comprises a subset of Spanish SMEs, since analysis thereof is of particular importance within this field given that these firms –together with self-employed workers– were the main target of guarantees/aid from the government because of the COVID-19 pandemic (ICO, 2020). Following the recommendation of the European Commission 2003/361/CE, we consider SMEs to be organizations that meet the following three requirements: (a) businesses with less than 250 employees; (b) whose annual turnover does not exceed €50 million; and (c) whose assets do not exceed €43 million. We specifically took SMEs included in the SABI (*Iberian Balance Analysis System*) database. This study does not cover all Spanish SMEs included in this database since we implement a double filter: first, we include SMEs belonging to sectors that concentrate most guarantees/aid[2]. These six sectors are: electricity, gas, and water (sector 03); manufacturing (sector 04); construction (sector 05); commerce, hotels, and catering

[2] See the reports published in https://www.ico.es/web/guest/ico/informes-seguimiento-linea-avales

(sector 06); transport and communications (sector 07); and education, health, and others (sector 09).

Second, in order to increase the quality and homogeneity of our data, firms that meet some of the following criteria are excluded: (i) micro-enterprises, given that the quality of the economic-financial data of these firms is often lower when compared to larger companies (Lopez-Gracia & Mestre-Barbera, 2011). For this reason, we exclusively focus on small and medium-sized companies (between 10 and 250 employees); (ii) companies involved in a bankruptcy or liquidation procedure. In this sense, SMEs whose assets have a negative value or one equal to zero are directly excluded (D'Amato, 2020); (iii) companies for which there is no information available for all years; and (iv) we removed extreme values, i.e., observations in the extreme 1% distribution at both tails for each variable in order to control for extreme values and outliers (Ashley & Yang, 2004; Chen et al., 2018).

After applying this double filter, our sample is composed of 3,305 Spanish SMEs, which are analyzed in the period between 2011 and 2020. Specifically, 2011-2017 is considered as a "control" period for estimating the optimal debt model since the relationship between optimal debt and its main determining factors during this period will not be influenced by government interventionist policies. Moreover, 2018-2020 is considered as the main period –where 2018 and 2019 are specifically considered as the "pre-COVID period" and 2020 is considered as the "COVID period". These three years were chosen because the comparison between 2018 and 2019 allows us to test pre-pandemic variations, while the comparison between 2020 and 2019 allows us to test COVID variations.

The distribution of SMEs by sectors is shown in Table 1. As can be seen, most of the SMEs are included within commerce, hotels, and catering (sector 06) and manufacturing (sector 04), and account for 37% and 20% of Spanish SMEs, respectively. In contrast, education, health, and others (sector 09) only represent 4% of SMEs.

Table 1. Sample distribution by sector

Sector	Definition	Number of companies	%
Sector 03	Electricity, gas, and water	492	15%
Sector 04	Manufacturing	659	20%
Sector 05	Construction	432	13%
Sector 06	Commerce, hotel, and catering	1213	37%
Sector 07	Transport and communications	383	11%
Sector 09	Education, health, and others	126	4%
		3,305	100%

2.3.2. Estimation of excess debt levels

In order to analyze to what extent there is excess debt (or an abnormal increase in debt) due to the COVID-19 pandemic, we first test whether excess debt in 2020 differs from zero (i.e., $H_0: \mu_{2020} = 0$; $H_A: \mu_{2020} \neq 0$). After that, we verify whether the possible mean differences between the COVID-year (i.e., 2020) and the pre-COVID period are significantly different from zero (i.e., $H_0: \mu_{2020} - \mu_{2109} = 0$; $H_A: \mu_{2020} - \mu_{2019} \neq 0$)[3]. For this purpose, we follow a two-stage procedure (Hovakimian et al., 2001).

In the first stage, as shown in Equation 1, debt levels are regressed on a vector of explanatory variables that are considered as the main determining factors of optimal debt levels for SMEs (Aybar-Arias et al., 2012; D'Amato, 2020; Lopez-Gracia & Mestre-Barbera, 2011; Lopez-Gracia & Sogorb-Mira, 2008; Serrasqueiro et al., 2012). We use a panel data method because it offers more information, greater efficiency, and greater

[3] Rather than performing regression analysis, we carry out this type of analysis because it is not possible to identify which specific SMEs received a public guarantee. As indicated in the limitations in the last section of this chapter, the ICO does not provide us with this information due to its confidentiality policy.

variability compared to other methods, thereby providing improvements in our econometric specifications and estimation (Balgati, 2001). This panel data is carried out for the control period (2011-2017) and is estimated for three different debt variables: total, short-term, and long-term debt. The purpose of this first stage regression is to obtain the estimation of coefficients (or beta) of each determining factor.

$$
\begin{aligned}
DEBT_{it} = \beta_0 + \beta_1 \cdot DEBT_{it-1} + \beta_2 \cdot RISK_{it} + \beta_3 \cdot GROWTH_{it} + \beta_4 \cdot TANG_{it} + \beta_5 \cdot NDTS_{it} \\
+ \beta_6 \cdot SIZE_{it} + \beta_7 \cdot TAX_{it} + \beta_8 \cdot LIQUID_{it} + \beta_9 \cdot AGE_{it} + \beta_{10} \cdot ROA_{it} + n_i \\
+ d_t + \psi_i + e_{it}
\end{aligned}
\tag{1}
$$

As regards Equation 1, the dependent variables are alternatively: total debt level (TOTAL_DEBT), which is measured as the ratio of total liabilities to total assets of firm *i* in year *t*; short-term debt (ST_DEBT), which is measured as the ratio of short-term liabilities to total assets of firm *i* in year *t*; and long-term debt (LT_DEBT), which is measured as the ratio of long-term liabilities to total assets of firm *i* in year *t* (Aybar-Arias et al., 2012; Serrasqueiro et al., 2012). Beyond considering debt levels in the previous year, the following determining factors of optimal debt within SMEs are included as independent variables (e.g., Aybar-Arias et al., 2012; D'Amato, 2020; Lopez-Gracia & Mestre-Barbera, 2011; Lopez-Gracia & Sogorb-Mira, 2008; Serrasqueiro et al., 2012):

(1) *Default risk* (RISK), whose influence on debt levels may be mixed. A priori, leverage tends to be reduced as this risk is greater –in particular within SMEs since they are more prone to the risk of default. This default risk is often associated with the volatility of company profits or operating income. When this volatility increases, the likelihood of SME bankruptcy or failure is greater (D'Amato, 2020), thereby increasing the incentives to reduce debt (Aybar-Arias et al., 2012; Wald, 1999). However, when debt maturity increases, this relationship could become positive to the extent that "the sensitivity of the

(tax-deductible) default premium per unit time to risk increases with maturity, and tax shields on the default premium can be earned before bankruptcy costs are faced at maturity" (Wiggins, 1990, p. 384). Default risk is thus expected to be negatively (positively) associated with short-term debt (long-term debt). This variable is measured as the absolute value of the variation of operating profits of firm *i* in year *t* (Serrasqueiro et al., 2012).

(2) *Growth opportunities* (GROWTH) also affect debt level. Highly-leveraged SMEs with high growth opportunities –which often face a problem of underinvestment– are expected to renounce investment projects that have a positive net worth (Aybar-Arias et al., 2012; Lopez-Gracia & Sogorb-Mira, 2008; Myers, 1977). High-growth SMEs are also more likely to fail (compared to low-growth SMEs) and should thus be less leveraged (D'Amato, 2020). A negative relationship is therefore expected between growth opportunities and optimal debt levels. This variable is measured as the annual growth rate of the sales of firm *i* in year *t* (D'Amato, 2020).

(3) *Tangibility* (TAN), whose importance is due to the fact that tangible assets increase the solvency of SMEs, favoring their debt capacity (Aybar-Arias et al., 2012). This factor's impact on leverage should, nevertheless, be nuanced depending on debt maturity, since SMEs should adjust the maturity of their liabilities to the maturity of their assets (D'Amato, 2020). In this way, tangible assets are expected to be negatively (positively) associated with short-term debt (long-term debt). This variable is measured as the ratio of fixed assets to total assets of firm *i* in year *t* (Aybar-Arias et al., 2012; Serrasqueiro et al., 2012).

(4) *Non-debt tax shields* (NDTS), whose impact on debt levels is negative because firms try to reduce their tax burden by using NDTS instead of debt, thus avoiding unnecessary distress costs (Dammon & Senbet, 1988). In the case of SMEs, this factor

may represent the main alternative to reducing tax burdens since SMEs do not usually use debt as a tax shield, given their lower profitability (D'Amato, 2020). In this sense, we expect a negative impact between NDTS and optimal debt level. This variable is measured as the ratio of depreciation to fixed assets of firm *i* in year *t* (Aybar-Arias et al., 2012; Lopez-Gracia & Mestre-Barbera, 2011).

(5) *SME size* (SIZE) is also a relevant factor since, as firm size increases, SMEs have more collateral guarantees and are more diversified, which translates into less risk for lenders (Titman & Wessels, 1988). Size is thus associated with a better reputation and positively influences SMEs' ability to achieve higher debt levels (Aybar-Arias et al., 2012). A positive relationship is thus expected between SME size and optimal debt levels. This variable is measured as the natural logarithm of total sales of firm *i* in year *t* (Aybar-Arias et al., 2012).

(6) *Effective tax rate* (TAX), whose impact on debt levels is due to the deductibility of interest payments. In this sense, the use of debt as a source of financing has a clear advantage, i.e., a reduction in income tax. The effective tax rate is thus expected to have a positive influence on optimal debt (Lopez-Gracia & Sogorb-Mira, 2008). This variable is measured as the ratio of income tax paid to profits before taxes and after interest of firm *i* in year *t* (Serrasqueiro et al., 2012).

(7) *Liquidity* (LIQUID), whose impact tends to differ depending on debt maturity. In the long term, liquidity represents a guarantee for long-term lenders. Consequently, SMEs may decide to remain liquid in order to improve their long-term creditworthiness. In the short term, SMEs can use their most liquid assets to finance their business opportunities, thus reducing debt levels (D'Amato, 2020). In this sense, the impact of liquidity on optimal debt is negative (positive) in the case of short-term debt (long-term

debt). This variable is measured as the ratio of current assets to current liabilities of firm *i* in year *t* (D'Amato, 2020).

(8) *SME age* (AGE) also influences debt level, since older SMEs have had more time to accumulate funds and thus have less need for external resources (Mac an Bhaird & Lucey, 2010). A negative association between age and optimal debt levels is therefore expected. This variable is measured as the natural log of the age of firm *i* in year *t* (D'Amato, 2020).

(9) *SME financial performance* (ROA). The most profitable businesses are expected to take on less debt since they are capable of generating funds internally (D'Amato, 2020; Fama & French, 2002). This effect is especially relevant within SMEs since they are more likely to suffer financial constraints in credit markets –facing the typical problems of adverse selection and moral hazard– which makes them resort mainly to internal resources (Aybar-Arias et al., 2012). We can thus expect financial performance to negatively affect optimal debt. This variable is measured as the ratio of operating income to total assets of firm *i* in year *t* (Aybar-Arias et al., 2012; Lopez-Gracia & Sogorb-Mira, 2008).

In the second stage, the coefficients estimated from Equation 1 are used to predict optimal debt levels (D_{it}^{*}) for 2018-2020 –where those factors determining optimal debt are again included. Specifically, as mentioned above, 2018 and 2019 are referred to as the "pre-COVID" period, while 2020 is referred to as the "COVID" period. After predicting optimal levels, we calculate the difference between this optimal debt (D_{it}^{*}) and the real (observed) debt ($DEBT$) for these three years. Such prediction errors measure excess debt (i.e., the level of debt not explained by the main determining factors of debt levels). More specifically, we define excess total debt (EXCESS_TOTAL_DEBT) as the difference between the actual (observed) level of debt of firm *i* in year *t* and the optimal (estimated) debt level of that firm and in that year; excess short-term debt (EXCESS_ST_DEBT) as the difference between the actual (observed) level of short-term debt of firm *i* in year *t* and the optimal (estimated) debt level of that firm and in that year; and excess long-term debt (EXCESS_LT_DEBT) as the difference between the actual (observed) level of long-term debt of firm *i* in year *t* and the optimal (estimated) debt level of that firm and in that year. We expect excess debt in 2020 to differ significantly from zero due to the Spanish government's interventionist policy and we also expect possible increases in excess debt between 2020 and prior years to be different from zero.

2.3.3. Efficiency in the allocation of public guarantees

We then examine whether the allocation of public guarantees has proved to be efficient or not –i.e., whether this aid has been allocated to SMEs that have suffered temporary distress after the COVID-19 pandemic. To address this issue, we regress excess debt for 2020 –calculated and defined as indicated in the previous Section 3.2 and which reflects the Spanish government's interventionist policy– on the annual variations of the main economic-financial indicators affected by COVID-19 and the nature of the distress suffered by SMEs, as stated in Equation 2. Following Baum et al. (2003), we also use a panel data method, but apply an extended instrumental variable estimation routine that provides generalized method of moments (GMM) estimation, introduced by Hansen (1982). This estimation allows for internally generated instruments –considering company history– in order to control endogeneity issues (Nadeem, 2022). It is also useful both for resolving many sources of endogeneity and for considering the potential dynamic nature of the relationships (Nadeem, 2022). We therefore deal with endogeneity by obtaining consistency in the presence of arbitrary heteroskedasticity and we test instrument subset validity through additional diagnostic tests.

$$EXCESS\ DEBT_{i,2020} = \beta_0 + \beta_1 \cdot \Delta RISK_{i,2019-2020} + \beta_2 \cdot \Delta GROWTH_{i,2019-2020} + \beta_3 \cdot \Delta NDTS_{i,2019-2020} + \beta_4 \cdot \Delta ROA_{i,2019-2020} + \beta_5 \cdot DISTRESS_{i,2020} + \beta_6 \cdot Control\ variables + e_{it} \quad (2)$$

As stated in Equation 2, our dependent variable is excess debt level –alternatively considering excess total ($EXCESS\_TOTAL\_DEBT_{it}$), short-term ($EXCESS\_ST\_DEBT_{it}$), and long-term debt ($EXCESS\_LT\_DEBT_{it}$), previously defined in Section 3.2. Moreover, our independent variables are the variations in the main economic factors that are potentially affected by this health crisis, i.e., the annual growth rate (between 2019 and 2020) in risk default, growth opportunities, non-debt tax shields, and performance. In this sense, $\Delta RISK_{i,2019-2020}$ refers to the variation experienced in risk default ratio –measured as the absolute value of the variation of operating profits (Serrasqueiro et al., 2012)– between 2019 and 2020; $\Delta GROWTH_{i,2019-2020}$ refers to the variation experienced in growth opportunities ratio –measured as the annual growth rate of sales (D'Amato, 2020)– between 2019 and 2020; $\Delta NDTS_{i,2019-2020}$ refers to the variation experienced in NDTS –measured as the ratio of depreciation to fixed assets (Aybar-Arias et al., 2012; Lopez-Gracia & Mestre-Barbera, 2011)– between 2019 and 2020; and $\Delta ROA_{i,2019-2020}$ refers to the variation experienced in financial performance (ROA) –measured as the ratio of operating income to total assets (Aybar-Arias et al., 2012; Lopez-Gracia & Sogorb-Mira, 2008)– between 2019 and 2020. In this sense, allocation of public aid may be considered efficient when excess debt is negatively influenced by growth opportunities, non-debt tax shields, or performance, and when it is positively influenced by risk default.

In addition, and more importantly, we include as an independent variable the nature of the (potential) decline suffered by each SME –since this is required in order to determine whether public aid was indeed directed at SMEs who suffered a temporary downswing. The nature of distress ($DISTRESS_{it}$) is a dichotomous variable that takes the value 1 when SMEs suffer "temporary" distress, and the value 0 when they suffer "structural" distress. For this division, we use the z-score indicator, which is used as a measure of financial risk or distress within the SME context (Altman & Sabato, 2007; Dolz et al., 2019; Lagazio et al., 2021; McGuinness et al., 2018). Specifically –as stated in Equation 3– we used Altman's z-score model which, although initially designed by Altman (1968) for publicly traded firms, was later adapted for private firms by Altman & Sabato (2007).

$$\begin{aligned} Altman\ z-score_{it} &= \sum 0.717 \cdot \frac{working\ capital_{it}}{total\ assets_{it}} + 0.847 \cdot \frac{retained\ earnings_{it}}{total\ assets_{it}} + 3.107 \\ &\cdot \frac{EBITDA_{it}}{total\ assets_{it}} + 0.42 \cdot \frac{book\ value\ of\ equity_{it}}{total\ liabilities_{it}} + 0.998 \cdot \frac{firm\ sales_{it}}{total\ assets_{it}} \end{aligned} \tag{3}$$

Based on Equation 3, we use the sector-average z-score as the threshold. SMEs above this threshold in year *t* are considered as not suffering distress, while SMEs below or equal to this threshold in year *t* are considered as suffering distress. As can be seen in Table 2, we classify SMEs suffering "temporary" deterioration as those who did not suffer deterioration prior to COVID-19 but who did suffer deterioration due to the pandemic; while we consider SMEs that suffer "structural" deterioration to be those who suffered deterioration prior to COVID-19 and who continued to suffer it as a result of the pandemic. In any other case, we consider that the SME does not suffer deterioration and it is therefore not taken into account for this analysis. We thus expect β_5 to be significant and positive, since excess debt (linked to liquidity injections) should be related to SMEs suffering temporary distress –which would imply efficient allocation of public guarantees in that the injection of liquidity is aimed at counteracting short-term deterioration, as required by the call for this public aid.

Table 2. Classification of SMEs according to the deterioration suffered

Type of deterioration	Dummy value	Description
Temporary	1	An SME is classified in this category if it meets the following two conditions: i) it did not suffer deterioration prior to COVID-19 (i.e., sector-average z-score in 2019 is above this threshold). ii) it did suffer deterioration due to COVID-19 (i.e., sector-average z-score in 2020 is below or equal to this threshold).
Structural	0	An SME is classified in this category if it meets the following two conditions: i) it did suffer deterioration prior to COVID-19 (i.e., sector-average z-score in 2019 is below or equal to this threshold). ii) it also suffered deterioration due to COVID-19 (i.e., sector-average z-score in 2020 is below or equal to this threshold).
No deterioration	Not included	The SME is classified in this category if it meets the following condition: It did not suffer deterioration due to COVID-19 (i.e., sector-average z-score in 2020 is above this threshold).

2.4. RESULTS

2.4.1. Descriptive statistics, correlations, and temporal evolution of the main variables

Table 3 shows the main statistics of our variables. In average terms, Spanish SMEs have a level of total debt equal to 29.19% –where 10.82% corresponds to short-term debt and 18.36% to long-term debt. Furthermore, the risk of bankruptcy (measured through the Altman z-score) shows an average value of 2.74, which places our SMEs within a "grey zone" –with a slight risk of suffering insolvency. Moreover, the liquidity ratio shows an average value of 1.89. However, its high standard deviation indicates high dispersion among data. Finally, Table 3 also includes the statistics of the remaining determining factors of optimal debt.

Table 3. Descriptive statistics of variables (2011-2020)

Variable	Mean	Median	SD	Min	Max
TOTAL_DEBT	0.2919	0.2778	0.1700	0.0108	0.7791
ST_DEBT	0.1082	0.0777	0.0995	0.0002	0.4786
LT_DEBT	0.1836	0.1525	0.1409	0.0017	0.6673
Z-SCORE	2.7419	2.6317	0.9162	0.8044	6.5562
RISK	0.8010	0.3479	1.3378	0.0000	11.8237
GROWTH	0.0259	0.0216	0.1673	-0.5510	0.7258
TANG	0.4335	0.4141	0.2214	0.0368	0.9574
NDTS	0.1078	0.0845	0.0822	0.0067	0.5148
SIZE	14.5382	14.5443	0.6411	12.7861	16.2732
TAX	-0.1636	-0.1759	0.1365	-0.9566	0.7926
LIQUID	1.8891	1.5450	1.2397	0.2160	9.8560
AGE	3.1118	3.1781	0.3941	1.7918	4.0254
ROA	3.2909	2.0790	5.2202	-17.8490	25.0380
DISTRESS	0.2001	0.0000	0.4002	0.0000	1.0000

Beyond showing descriptive statistics, analyzing how the main debt, liquidity, and solvency indicators evolved year after year is of specific interest. Of particular importance is examining the changes that occurred between 2019 and 2020 so as to determine the effects of the COVID-19 pandemic. Table 4 shows a large increase in total debt levels between 2019 and 2020, where a growth of about five percentage points is experienced. This increase –which means returning to debt levels close to those experienced after the last economic recession of 2008– may be conditioned by the interventionist policy deployed by the Spanish government to mitigate the effect of COVID-19. By considering debt maturity, Table 4 shows how, while long-term debt experiences substantial growth between 2019 and 2020 (from 16.00% to 21.68%), short-term debt decreases slightly (from 11.56% to 9.37%), which can also be seen in Figure 1. This different evolution of short- and long-term debt is caused by the change in debt structure –defined as the ratio of long-term liabilities to short-term liabilities of firm *i* in year *t*– due to the substitution of bank guarantees (short-term) for public guarantees (long-term) –as seen in Figure 2.

Table 4. Evolution of levels of debt, insolvency, and liquidity (2011-2020)

Year	TOTAL_DEBT (%)	ST_DEBT (%)	LT_DEBT (%)	Z-SCORE	Annual change in Z-SCORE (%)	LIQUID
2011	30.55	10.87	19.69	2.68	2.76	1.77
2012	30.01	10.48	19.53	2.66	1.06	1.82
2013	29.53	10.59	18.95	2.67	3.19	1.83
2014	29.20	10.46	18.74	2.70	4.08	1.84
2015	29.23	10.95	18.18	2.76	3.99	1.86
2016	28.77	11.06	17.82	2.78	2.59	1.86
2017	28.15	11.15	17.08	2.79	2.64	1.83
2018	28.31	11.62	16.69	2.83	3.31	1.87
2019	27.56	11.56	16.00	2.88	2.99	1.89
2020	31.06	9.37	21.68	2.63	-9.83	2.32

Table 4 also shows the temporal evolution of the z-score and liquidity ratio. We see a drop in the z-score between 2019 and 2020, which translates to an increase in SME bankruptcy risk due to the COVID-19 pandemic. This interrupts the favorable trend this indicator had experienced following the last recession. For its part, the liquidity ratio experienced a marked increase between 2019 and 2020 –much higher than any increase in this period– and that may be due to the Spanish government's interventionist policy, which involved large injections of liquidity in an effort to mitigate the unfavorable economic consequences of the COVID-19 pandemic.

Figure 1. Evolution of debt levels (2010-2020)

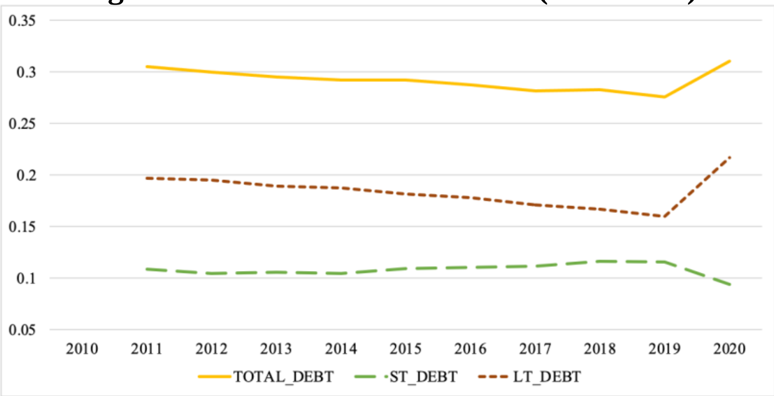
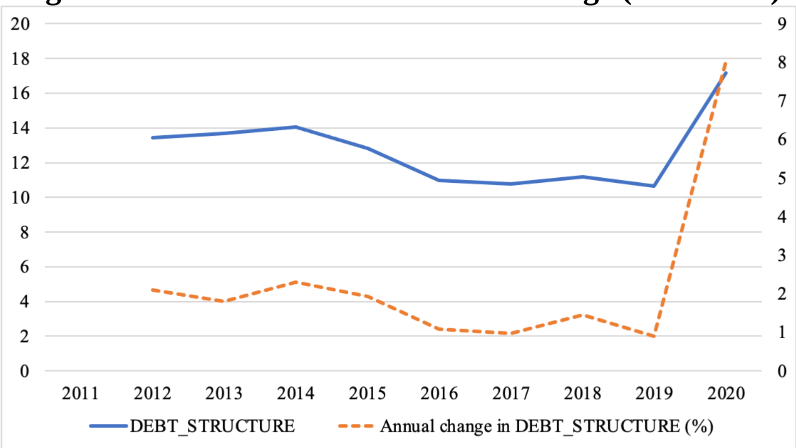


Figure 2. Debt structure and annual change (2011-2020)



Finally, Table 5 contains the matrix of correlations of the variables included in this study. Prominent are the correlations between debt variables –in particular the positive correlation between total debt and short/long-term debt. The negative correlation between short-term and long-term debt is also noticeable. For its part, there are negative correlations between debt variables and z-score, and between debt variables and liquidity ratio. The VIF values show that no multicollinearity problems were identified.

Table 5. Correlations matrix – Pearson coefficients (2011-2020)

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	VIF
(1) TOTAL_DEBT	1.0000														-
(2) ST_DEBT	0.5605***	1.0000													1.40
(3) LT_DEBT	0.8109***	-0.0302***	1.0000												1.64
(4) Z-SCORE	-0.5977***	-0.2880***	-0.5180***	1.0000											2.87
(5) RISK	-0.0343***	-0.0501***	-0.0059	0.0234***	1.0000										1.30
(6) GROWTH	-0.0301***	-0.0072	-0.0313***	0.1085***	0.0384***	1.0000									1.40
(7) TANG	0.2890***	-0.1104***	0.4268***	-0.3214***	0.0294**	-0.0274***	1.0000								1.45
(8) NDTS	-0.1214***	-0.0162**	-0.1351***	0.3475***	0.0345***	0.0243***	-0.3397***	1.0000							1.26
(9) SIZE	0.0327***	0.0244***	0.0222***	-0.3169***	-0.0679***	0.0021	0.0861***	-0.2244***	1.0000						1.32
(10) TAX	0.0060	-0.1597***	0.1538***	-0.1786***	-0.0760***	0.0097	0.0149**	0.0007	0.0225***	1.0000					1.06
(11) LIQUID	-0.3476***	-0.3796***	-0.1513***	0.3549***	0.0330***	-0.0821***	-0.2990***	0.1064***	0.1275***	-0.0966***	1.0000				1.54
(12) AGE	-0.0843***	0.0112**	-0.1097***	-0.0149**	0.0010	-0.0497***	-0.0397***	-0.0862***	0.2410***	-0.0141**	0.1169***	1.0000			1.06
(13) ROA	-0.2473***	-0.1999**	-0.1573***	0.3814***	-0.0796***	0.2433***	-0.0642***	0.0955***	0.0344***	-0.1295***	0.1443***	-0.0616***	1.0000		1.80
(14) DISTRESS	-0.1782***	-0.1830***	-0.0832***	0.3992***	-0.0082	-0.1739***	-0.2028***	0.1572***	-0.2123***	-0.0639***	0.2152***	-0.0647*	-0.0366	1.0000	1.42

***p-value < 0.01; ** p-value < 0.05; * p-value < 0.10

2.4.2. Effects of the Spanish government's interventionist policy on debt levels

Table 6 contains the estimation of optimal debt model (from Equation 1) for the control period (2011-2017). In our sample, the determining factors for optimal debt levels display the expected behavior, in line with prior literature –considering both total debt, and when distinguishing between short- and long-term debt. More specifically, regardless of debt maturity, the determining factors that positively influence optimal debt are effective tax rate, firm size, and debt levels of the previous year, while growth opportunities, non-debt tax shields, firm age, and probability exert a negative influence. Moreover, the impact of default risk, tangibility, and the liquidity rate vary depending on debt maturity –i.e., while these factors negatively influence short-term debt levels, their influence is positive in terms of long-term debt.

We then compare actual (observed) debt and optimal debt for the 2018-2020 period in order to obtain the levels of excess debt for those years. As noted below, 2018 and 2019 refer to the "pre-COVID" period, while 2020 refers to the "COVID" period. Table 7 shows the means for optimal debt levels (calculated from the coefficients estimated for our control period in Table 6) and for excess debt levels (calculated from the difference between actual and optimal debt). As can be seen in Table 7, we see how optimal total and long-term debt levels for 2020 are slightly higher than for 2018 and 2019, while optimal short-term debt levels for 2020 are slightly lower than in previous years. For their part, we also see how excess debt levels are higher and considerably different from the optimum in 2020. Moreover, after calculating the differences regarding excess debt, we see how variations are much more pronounced during the COVID period. Specifically, excess long-term debt increases by five percentage points (from -0.62 in

2019 to 4.63 in 2020), while excess short-term debt falls by about two percentage points (from 1.17 in 2019 to -1.06 in 2020).

Table 6. Determining factors of optimal debt (2011-2017)

	Expected sign	$DEBT_t$	Expected sign	ST_DEBT_t	Expected sign	LT_DEBT_t
$TOTAL\_DEBT_{t-1}$	+	0.3781^{***}				
ST_DEBT_{t-1}			+	0.2520^{***}		
LT_DEBT_{t-1}					+	0.2476^{***}
$RISK_t$	+/-	0.0011^{**}	-	0.0002	+	0.0010^{**}
$GROWTH_t$	-	-0.0129^{***}	-	-0.0183^{***}	-	-0.0059^{**}
$TANG_t$	+/-	0.1694^{***}	-	-0.1243^{***}	+	0.2957^{***}
$NDTS_t$	-	-0.1053^{***}	-	-0.0379^{***}	-	-0.0651^{***}
$SIZE_t$	+	0.1468^{***}	+	0.0314^{***}	+	0.1182^{***}
TAX_t	+	0.0168^{***}	+	0.0105^{***}	+	0.0090^{**}
$LIQUID_t$	+/-	0.0076^{***}	-	-0.0320^{***}	+	0.0382^{***}
AGE_t	-	-0.1330^{***}	-	-0.0054	-	-0.1294^{***}
ROA_t	-	-0.0038^{***}	-	-0.0017^{***}	-	-0.0022^{***}
Constant		-1.6071^{***}		-0.2363^{***}		-1.3856^{***}
Year control		Yes		Yes		Yes
Sector control		Yes		Yes		Yes
R (within)		0.3916		0.2173		0.4369
R (between)		0.3257		0.5524		0.2944
R (overall)		0.3395		0.4145		0.3210
F statistic		497.47^{***}		214.55^{***}		599.60^{***}

***p-value < 0.01; ** p-value < 0.05; * p-value < 0.10

In addition, Table 7 contains several different tests to check whether debt excesses are statistically different from 0 for 2020 (see column III) and whether the differences in means are statistically significant between pre-COVID and COVID periods (see columns IV-V). Results show that excess debt is significantly different from zero after the onset of the pandemic, which means that observed debt levels differ from optimal ones. Moreover, excess short-term debt was positive and excess long-term debt was negative for 2018-2019. Nevertheless, as a consequence of COVID-19, excess short-term debt turned negative in 2020 while excess long-term debt turned positive. This behavior is consistent with the change experienced by debt structure in 2020 (see Figure 2), disproportionately increasing excess long-term debt, which has meant that in global terms total excess debt has also increased. In addition, after testing the differences in means in the pre-COVID period ($\Delta_{2019\text{-}2018}$) and in the COVID period ($\Delta_{2020\text{-}2019}$), we find no significant differences in excess debt means in the period prior to the pandemic, while these differences do prove to be statistically significant after the onset of COVID-19.

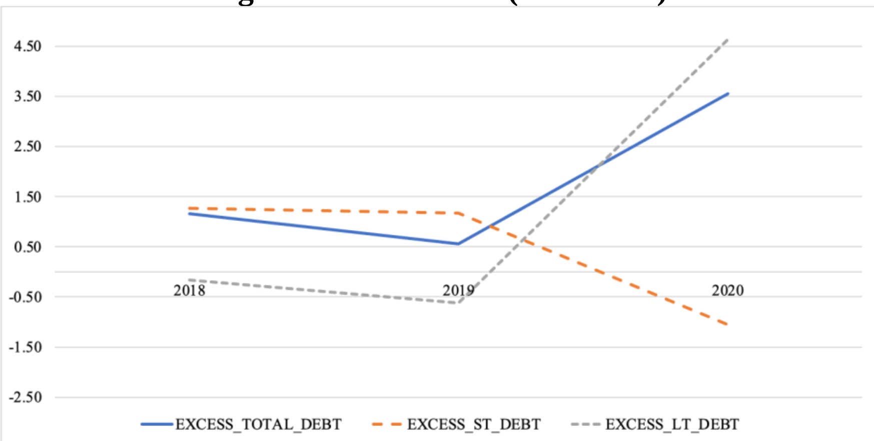
Table 7. Optimal debt levels and debt excess (2018-2020)

		2018	2019	2020	$\Delta_{2019\text{-}2018}$	$\Delta_{2020\text{-}2019}$
TOTAL_DEBT	OPTIMAL_TOTAL_DEBT	0.2757	0.2743	0.2777		
	EXCESS_TOTAL_DEBT (%)	1.1639	0.5624	3.5463***	-0.6014	2.9839***
ST_DEBT	OPTIMAL_ST_DEBT	0.1071	0.1084	0.1047		
	EXCESS_ST_DEBT (%)	1.2703	1.1711	-1.0584***	-0.0992	-2.2294***
LT_DEBT	OPTIMAL_LT_DEBT	0.1693	0.1658	0.1724		
	EXCESS_LT_DEBT (%)	-0.1651	-0.6188	4.6321***	-0.4536	5.2393***

***p-value < 0.01; ** p-value < 0.05; * p-value < 0.10

More visually, the progression of excess debt in the 2018-2020 period is shown in Figure 3, where a noticeable increase in excess long-term debt is evident, whereas excess short-term debt falls. All of this allows us to state that, after the Spanish government interventionist policy, levels of excess debt increased in 2020, deviating from the optimum. This is especially marked in the case of excess long-term debt –which is in fact the time horizon that characterizes the public guarantees aimed at mitigating the adverse economic effects caused by this pandemic. For its part, the drop in excess short-term debt in 2020 may be explained by the transformation of short-term banking guarantees into long-term public guarantees.

Figure 3. Excess debt (2018-2020)



As a complement to the previous analyses, and in order to provide robustness to our results, in Table 8 we perform a new regression of optimal debt on its main determining factors considering the whole period (i.e., 2011-2020), and introducing a dummy variable to control the specific role played by the year 2020 within this panel data regression[4]. As can be seen, the behavior of the main determinants of optimal debt is identical to that obtained in Table 6. In addition, the impact of year 2020 is positive and significant in the case of total and long-term debt, while this impact turns negative in the

[4] For this purpose, a dummy variable is created that takes the value 1 when the year is 2020, and the value 0 when the year is any other than 2020.

case of short-term debt. These results are consistent with those obtained in Table 7 and again show the effect of the Spanish government's interventionist policy on debt levels as well as the change experienced by debt structure, thereby providing robustness to our prior evidence.

Table 8. Robustness test. Determining factors of optimal debt (2011-2020)

	Expected sign	$DEBT_t$	Expected sign	ST_DEBT_t	Expected sign	LT_DEBT_t
$TOTAL\_DEBT_{t-1}$	+	0.5079***				
ST_DEBT_{t-1}			+	0.3516***		
LT_DEBT_{t-1}					+	0.4657***
$RISK_t$	+/-	0.0017***	-	-0.0002	+	0.0021**
$GROWTH_t$	-	-0.0179***	-	-0.0169***	-	0.0000
$TANG_t$	+/-	0.0811***	-	-0.1192***	+	0.2020***
$NDTS_t$	-	-0.1565***	-	-0.0478***	-	-0.1083***
$SIZE_t$	+	0.1106***	+	0.0266***	+	0.0887***
TAX_t	+	0.0136***	+	0.0077***	+	0.0096***
$LIQUID_t$	+/-	0.0051***	-	-0.0295***	+	0.0321***
AGE_t	-	-0.0975***	-	-0.0256***	-	-0.1261***
ROA_t	-	-0.0040***	-	-0.0018***	-	-0.0024***
Year 2020	+/-	0.0030***	-	-0.0227***	+	0.0542***
Constant		-1.1774***		-0.2750***		-0.9315***
Sector control		Yes		Yes		Yes
R (within)		0.4641		0.2993		0.4795
R (between)		0.5418		0.6400		0.4166
R (overall)		0.5386		0.5809		0.4427
F statistic		1530.32***		754.87***		1627.70***

***p-value < 0.01; ** p-value < 0.05; * p-value < 0.10

After carrying out this analysis by sectors, we see that all of them display similar behavior in terms of excess debt –as shown in Table 9 and Figures 4 a-c. The largest increases in excess long-term debt were experienced in commerce, hotel, and catering (sector 6) and in education, health, and other services (sector 9). However, the increase in excess long-term debt is less striking in transport and communications (sector 07). As regards excess short-term debt, the biggest drop occurs in manufacturing (sector 4) and commerce, hotel, and catering (sector 6), while the least impact occurs in education, health, and other services (sector 9). These results are consistent with the data offered by the ICO regarding the distribution of guarantees by sector (ICO, 2020). Moreover, we see how debt excesses are significantly different from zero in 2020 (see column III). In most sectors, the change experienced in debt structure is similar to that previously mentioned for Table 07, i.e., the health crisis tended to trigger long-term debt excesses while turning short-term debt excesses into negative ones. Finally, as expected, the differences in means for all excess debt levels are statistically significant in the COVID period ($\Delta_{2019\text{-}2020}$), while there are no significant differences in excess debt means in the pre-pandemic period ($\Delta_{2018\text{-}2019}$).

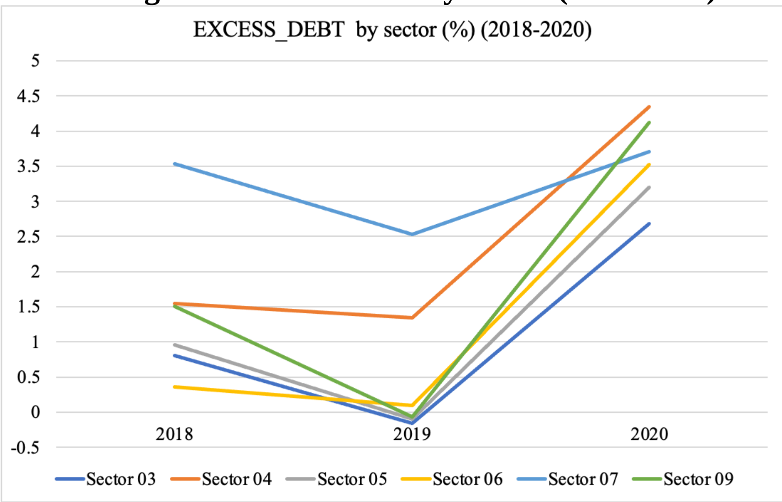
Table 9. Excess debt by sector (2018-2020)

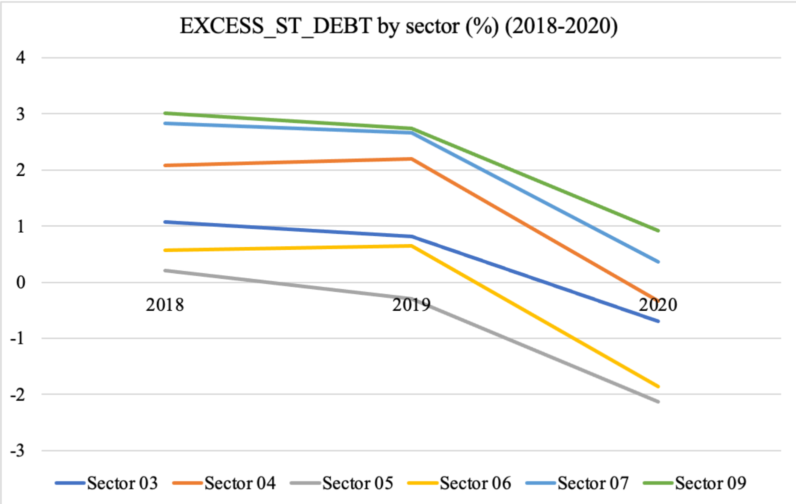
Sector[a] / Excess debt		2018	2019	2020	$\Delta_{2019-2018}$	$\Delta_{2020-2019}$
EXCESS_TOTAL_DEBT (%)	Sector 03	0.8088	-0.1604	2.6772***	-0.9692	2.8376***
	Sector 04	1.5450	1.3450	4.3468***	-0.1999	3.0018***
	Sector 05	0.9610	-0.0933	3.1961***	-1.0543	3.2894***
	Sector 06	0.3631	0.0926	3.5254***	-0.2705	3.4328***
	Sector 07	3.5331	2.5284	3.7092***	-1.0052	1.1813
	Sector 09	1.5001	-0.0632	4.1179**	-1.5633	4.1811*
EXCESS_ST_DEBT (%)	Sector 03	1.0701	0.8112	-0.7033**	-0.2589	-1.5146***
	Sector 04	2.0770	2.1911	-0.3344	0.1141	-2.5255***
	Sector 05	0.2107	-0.2979	-2.1280***	-0.5086	-1.8301***
	Sector 06	0.5714	0.6505	-1.8646***	0.0790	-2.5151***
	Sector 07	2.8251	2.6559	0.3648	-0.1692	-2.2912***
	Sector 09	3.0039	2.7373	0.9167	-0.2667	-1.8206*
EXCESS_LT_DEBT (%)	Sector 03	-0.3694	-1.0642	3.2985***	-0.6948	4.3627***
	Sector 04	-0.4406	-0.7007	4.8996***	-0.2601	5.6003***
	Sector 05	0.5461	0.0969	5.2051***	-0.4492	5.1082***
	Sector 06	-0.3311	-0.6333	5.5368***	-0.3022	6.0011***
	Sector 07	0.7958	0.0050	3.4461***	-0.7908	3.4411***
	Sector 09	-1.5609	-2.7953	3.1384*	-1.2345	5.9370**

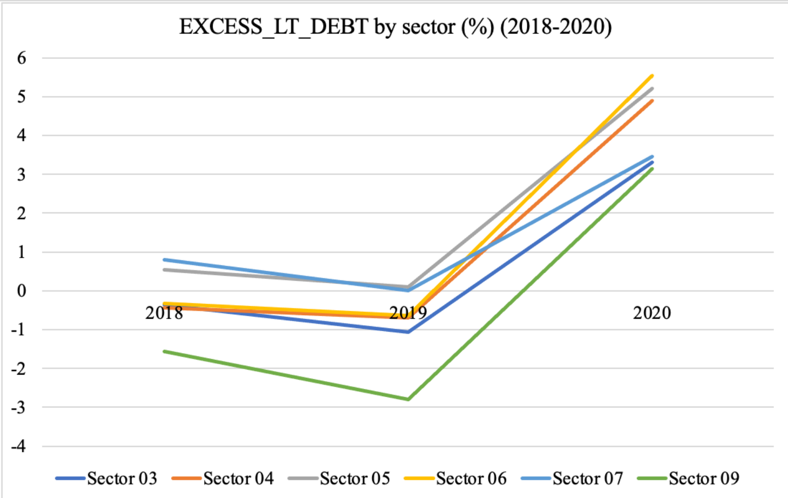
***p-value < 0.01; ** p-value < 0.05; * p-value < 0.10

[a]Sector 03 (Electricity, gas, and water); Sector 04 (Manufacturing); Sector 05 (Construction); Sector 06 (Commerce, hotel, and catering); Sector 07 (Transport and communication); and Sector 09 (Education, health, and others).

Figures 4. Excess debt by sector (2018-2020)







2.4.3. Analysis of efficiency in the allocation of public guarantees

Table 10 shows those factors that may explain changes in the levels of excess (total, short-term, and long-term) debt in 2020 after the outbreak of the COVID-19 pandemic. We see that excesses in total debt are mainly related to a drop in firm profitability. For its part, excessive long-term debt (which is more relevant given that this is the time horizon for public guarantees/aid) is related with an increase in default risk and a decline in firm profitability. It would therefore initially appear that this public aid was directed towards distressed companies in the sense that there is a positive relationship between excess long-term debt (potentially explained by the injection of liquidity due to the government's interventionist policy) and SMEs' economic-financial downturn.

Table 10. Determining factors of debt excess caused by COVID-19

	EXCESS_TOTAL_DEBT 2020	EXCESS_ST_DEBT 2020	EXCESS_LT_DEBT 2020
ΔRISK	0.0001	-0.0001	0.0001*
ΔGROWTH	-0.0001	-0.0000	-0.0001
ΔNDTS	-0.0002	-0.0011	0.0001
ΔROA	-0.0018***	-0.0001	-0.0013***
ΔSIZE	-0.1389***	-0.0189***	-0.1231***
ΔAGE	0.0987***	0.0087**	0.0905***
Constant	1.7630***	0.2340***	1.5499***
Sector control	Yes	Yes	Yes
R-squared	0.3417	0.0525	0.2723
F statistic	119.32***	13.64***	86.30***

***p-value < 0.01; ** p-value < 0.05; * p-value < 0.10

After verifying that this injection of liquidity was indeed aimed at SMEs who experienced distress, it is necessary to go a step further and to assess to what extent these SMEs suffered either temporary or structural distress. This is a relevant issue since, in line with the objective of these public guarantees, such support should have been aimed at remedying temporary problems rather than solving structural problems. The results shown in Table 11 indicate that banks (who were in charge of distributing Spanish government support) were unable to direct public aid to the SMEs that suffered a temporary downswing due to this health crisis. In fact, contrary to our expectations, our results show that excess debt is negatively related to the temporary nature of the decline, which implies that SMEs suffering a temporary downswing are less likely to have excess debt (which may be explained by the lower injection of liquidity received). In other words, excess debt is more related to SMEs who suffered structural distress. Adequate discriminatory capacity was not therefore exercised when allocating these public guarantees/aid, such that the aim of directing said support towards SMEs who suffered a temporary decline caused by COVID-19 was not fulfilled.

Table 11. Efficiency in the allocation of public guarantees (temporary *versus* structural distress)

	EXCESS_TOTAL_DEBT 2020	EXCESS_ST_DEBT 2020	EXCESS_LT_DEBT 2020
ΔRISK	0.0001	0.0001	0.0004*
ΔGROWTH	-0.0001	0.0000	-0.0002
ΔNDTS	-0.0053	-0.0013	-0.0040
ΔROA	-0.0012***	-0.0001	-0.0010**
ΔSIZE	-0.1439***	-0.0224***	-0.1302***
ΔAGE	0.1016***	0.0171**	0.0947***
DISTRESS	-0.1149***	-0.1278***	-0.1298***
Constant	1.9283***	0.3057***	1.6755***
Sector control	Yes	Yes	Yes
R-squared	0.4009	0.0680	0.3314
F statistic	98.93***	11.68***	73.54***

***p-value < 0.01; ** p-value < 0.05; * p-value < 0.10

2.5. CONCLUSIONS

At a global level, major efforts had to be made by national governments to cushion the adverse effects of the COVID-19 pandemic (Kahn & Wagner, 2021) since most firms saw their normal functioning and operations altered, with some even teetering on the brink of bankruptcy (Cressy, 2006; Ghosal & Ye, 2015). Among these negative effects, the liquidity and solvency crisis –resulting from the abrupt drop in firms' sales and turnover– deserve special attention (Almeida, 2021; Blanco et al., 2021; Demmou et al., 2021; He et al., 2020). These government efforts mainly consisted of adopting public policies to contain firms' economic and financial distress and so prevent a further decline in the economy. In Spain, one of the key policies was the public guarantee policy, whose aim was to grant credit to companies so that they could continue to operate as normally as possible (ICO, 2020; *Real Decreto-Ley 25/2020, de 3 de julio, de medidas urgentes para apoyar la reactivación económica y el empleo*, 2020). This credit –targeted strictly at remedying short-term or temporary distress– was mainly directed towards SMEs and self-employed workers (ICO, 2020). In this context, by using a sample of Spanish SMEs, this work seeks, on the one hand, to gauge the effect of the liquidity injection (derived from this public policy) on SMEs' optimal debt, and on the other hand to examine to what extent the allocation of this public support (managed by banks) did or did not prove to be efficient, i.e., whether or not it managed to remedy temporary distress.

Our results lead to two important conclusions: firstly, these public guarantees triggered an increase in abnormal debt levels (in particular, in SMEs' long-term debt); secondly, their allocation was not efficient, since they were not mainly directed towards SMEs who suffered a temporary downswing caused by COVID-19. Based on these results, several reflections, which offer interesting contributions to the literature, may be made. First, this chapter shows how excess government intervention in the economy (in this case, through a large injection of liquidity) leads to significant alterations in SMEs' optimal debt thresholds, which increases the risk of default when repayment is due. These debt excesses are mainly due to the increase in long-term debt in 2020 –since public guarantees have a maturity of approximately five years. Although these public guarantees are useful in terms of preventing certain SMEs from going under (or, at least, reducing the severity of their economic decline), it is no less true that they have generated a distortion in optimal debt levels. One possible reason underlying this is that the injection of liquidity was extremely excessive –in fact, this program guaranteed over €64,120.8 million by the end of 2020 in SMEs (ICO, 2020). A more conservative stance should have been adopted by the Spanish government.

Second, this study contributes to the literature by showing how public guarantees were not mainly directed towards SMEs who suffered a decline classified as "temporary". This is not consistent with the main aim sought by the Spanish government –since this support was not meant to be allocated simply to firms suffering any type of distress. Rather, the spirit of this public policy was to channel liquidity towards firms suffering temporary downswings caused by the health crisis (ICO, 2020). We can thus state that allocation of this public aid was not efficient in the sense that, despite having been granted to certain weakened organizations, these companies did not suffer a short-term downswing. Third, allocation of public aid tends to be less efficient when channeled by private agents –such as banks– and when there are no clear criteria about which companies must benefit. In this regard, we see how banks, when handling the allocation of this "public" credit, tend to adopt riskier and more opportunistic behavior –compared to the behavior expected when managing private bank loans (Cordella et al., 2018; Gropp et al., 2014; Leonello, 2018), thereby adding fresh evidence in the context of a health crisis such as the COVID-19 pandemic.

Moreover, this chapter offers several practical implications. First, as regards SMEs, we highlight the importance of increasing corporate responsibility and awareness before resorting to such aid. In other words, the request for public support should be consistent with the distress suffered by each individual firm and with its ability to repay the amount requested, since taking on such major financial commitments increases the risk of bankruptcy. Second, at the government level, our results reveal that an excessive injection of liquidity, despite helping to reduce SMEs' liquidity crises, generates a substantial increase in debt levels, which translates to a greater risk of insolvency upon expiration of these guarantees. In this regard, some Spanish newspaper headlines have already expressed particular concern about the potential appearance of new default risks. Such headlines include "First alarms about the latent late payment in banking due to ICO loans" (Romero, 2022) or "The ICO 'bomb': the Government will not know the real late payment" (Cabrera, 2022). Moreover, when channeling of public aid is left in the hands of banks, far clearer and detailed guidelines are needed to avoid discretion in the allocation of public support. Greater delimitation of criteria might have favored support being channeled towards SMEs that were indeed temporarily suffering as a result of the COVID-19 pandemic. Finally, as for the banks, they should adopt a more prudent and co-responsible attitude when allocating public aid, since they tend to assume excessive risks and to act somewhat recklessly, which leads to a delicate situation that ends up being unfavorable both for the SMEs themselves and for the economy as a whole.

Finally, this research is not exempt from limitations, from which interesting lines for future research emerge. First, this study focuses on Spain and analyzes the impact of a specific public policy. Future studies might examine the impact of similar public policies using a cross-country approach. Second, this work focuses on the effects of public guarantees on debt levels in 2020. Future studies might expand this time horizon, in addition to exploring what impact they have on other relevant economic-financial factors for businesses. Third, this chapter examines the effect of public guarantees on SMEs. Future studies might therefore extend this analysis by considering a sample of larger companies. Finally, this study focuses on SMEs which belong to the sectors that concentrate most of this public funding. However, we are unable to specifically identify which SMEs received this support. This information was requested from the ICO, but the latter body did not provide the data due to its data protection policy. If able to identify which companies (in particular, SMEs) receive public guarantees, future studies might delve into their economic-financial viability and explore their capacity to meet repayment commitments.

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CHAPTER 3

ENVIRONMENTAL POLICY AND CARBON MARKETS: HOW EU-ETS VOLATILITY AFFECTS CORPORATE PERFORMANCE IN HIGH AND LOW EMISSION COMPANIES

ABSTRACT

This study analyzes the volatility spillover between European carbon market returns (i.e., EU-ETS returns) and the returns of European companies with varying emission levels. Specifically, it examines both short-term and long-term effects, focusing on high- and low-emission companies during the third and fourth phases of the EU-ETS (2013–2024). Using the dynamic connectedness index and frequency band decomposition, it assesses how carbon market shocks at different frequencies influence corporate returns. The results show significant and time-varying connectedness between EU-ETS returns and the returns of both high- and low-emitting companies, driven by regulatory changes aimed at decarbonization. Notably, carbon volatility transmission increases over time (specifically, over the third and fourth phase of the EU-ETS) and is similar across high- and low-emission companies, due in part to the sensitivity of the finance sector to EU-ETS shocks. We find that carbon acts as a volatility receiver, especially in energy-related sectors, with most spillovers occurring in the short term (1–5 days). These findings highlight the importance of carbon markets in shaping corporate financial performance and the need to understand volatility transmission under evolving environmental policies.

3.1. INTRODUCTION

Regulated carbon markets emerged as a result of the Kyoto Protocol, adopted in 1997 under the United Nations Framework Convention on Climate Change (UNFCCC) (United Nations, 1997), which came into effect in 2005 following Russia's ratification. The underlying idea of carbon markets is to use this market as a tool to reduce greenhouse gas (GHG) emissions. A price is set for carbon, and companies can trade permits or carbon credits to lower their GHG emissions. In this context, the Kyoto Protocol established binding targets for GHG reductions for industrialized countries, responding to the need to reduce GHG emissions, limit global warming, address climate change efficiently and effectively, and promote sustainable development on a global scale (Mor et al., 2023). Specifically, it was established that industrialized countries and developing countries would reduce pollutant emissions by at least 5.2% for the period 2008-2012, using 1990 as a reference year (Mata et al., 2013).

In the second phase of the Kyoto Protocol (2013-2020), the signatory countries committed to reducing emissions by at least 18%, again using 1990 as the reference year. The United States, Russia, and Canada did not sign this extension (BBVA, 2023). After it ended in 2020, it was replaced by the Paris Agreement, which emerged from the UN Climate Change Conference (COP21) in Paris (2015) (United Nations, 2015). Among its objectives is to keep the increase in global temperature below two degrees Celsius above pre-industrial levels and to enhance the capacity of countries to reduce their vulnerability to climate change, based on technological development and promotion (United Nations, 2015) as an alternative to acquire certified emission reductions at a lower cost than in their markets.

Considering this context, the development of carbon markets has been influenced by three key factors. First, the Clean Development Mechanism –see article 12 of the mentioned Kyoto Protocol (United Nations, 1997)– which allows industrialized countries and companies to subscribe to agreements to meet GHG reduction targets (2008-2012) by investing in emission reduction projects in developing countries as an alternative to acquiring certified emission reductions at a lower cost than in their markets. Secondly, the European Union Emission Trading System (EU-ETS), launched in 2005, which has become the world's first and largest carbon market. Thirdly, voluntary carbon markets (Bayer & Aklin, 2020; Orygen Earth, 2023), which developed alongside regulated markets, allowing individuals, companies, and organizations to purchase additional carbon credits, supporting projects that offset or reduce emissions.

Regulated carbon markets are then established by governments or international treaties to control and reduce GHG emissions. They allow companies and countries to meet their emission reduction targets by buying and selling carbon permits or credits, which represent the right to emit a certain amount of GHGs (Bayon et al., 2012). These markets create financial incentives for companies to invest in technologies and practices that lessen emissions. Those that emit less than allowed can sell their surplus permits, generating additional income, thereby encouraging businesses to adopt more sustainable practices to lower the environmental cost of their activities (Spanish Ministry for Ecological Transition and Demographic Challenge, 2024).

Directive 2003/87/EC establishes a scheme for trading GHG emission allowances in the European Union (EU) context (European Parliament, 2003). This is the cornerstone of EU policy to combat climate change by reducing GHG emissions in a cost-effective and economically efficient manner. The system is based on the principle of cap and trade. The original legislation has been amended several times as the system has evolved. The most recent changes were adopted in Directive (EU) 2023/958 (European Parliament, 2023a) and in Directive (EU) 2023/959 (European Parliament, 2023b) as part of the EU's Fit for 55 initiative (European Council, 2023), which aims to ensure that EU policies align with the commitments and climate objectives of European Climate Law within the framework of the European Green Deal (European Commission, 2023) and the Paris Agreement (United Nations, 2015).

Among the challenges facing the EU-ETS are the adjustment of carbon pricing to encourage significant reductions, carbon leakage control, the process of integrating with other global carbon markets, and alignment with the EU's ambitious climate goals –such as those in the European Green Deal. It is therefore pertinent to assess the extent to which the implementation of EU-ETS reforms aimed at meeting the climate objectives affects the transmission of carbon volatility to companies in sectors traditionally classified as high-emission and low-emission. This article thus seeks to analyze the transmission of volatility between the returns of the EU Emission Trading System (EU-ETS) and returns of European companies with high and low emissions, distinguishing between short-term and long-term effects. We specifically seek to investigate whether there is connectedness between the returns of EU-ETS and of those companies, the degree of that connectedness, whether it differs between the two types of companies, and whether it changes throughout the period encompassing the third and fourth phases of the EU-ETS (from 2013 to 2024). To achieve this, we apply the dynamic connectedness index developed by Diebold & Yilmaz (2009, 2012, 2014) combined with the decomposition of interdependence into frequency bands (Baruník & Křehlík, 2018) in order to measure the extent to which carbon shocks at different frequencies (short or long term) influence the returns of high- and low-emission companies.

By addressing these goals, this article makes several key contributions to current understanding of carbon market dynamics. First, unlike previous studies that primarily focus on market indices, this research centers on individual high- and low-emission companies, providing a more nuanced view of how carbon markets affect different types of firms. Second, it specifically investigates how recent environmental reforms in the EU influence volatility transmission, thereby offering valuable insights into the regulatory impact on financial markets and corporate behavior. Third, the study analyzes the evolution of volatility transmission from carbon markets over the third and fourth phases of the EU-ETS, highlighting how changes in market structure and regulatory adjustments have influenced market volatility over time. Finally, it compares the patterns of increased volatility transmission between high-emission and low-emission companies, illustrating how different levels of emissions exposure lead to varying impacts from carbon market fluctuations, which is critical for understanding the differential effects of environmental policies on firms.

The article is structured as follows. After this introduction, Section 2 compromises a literature review regarding this topic. Section 3 outlines the dynamic connectedness analysis by Diebold & Yilmaz (2009, 2012, 2014) and the decomposition of interdependence into frequency bands (Baruník & Křehlík, 2018). Data are then presented in Section 4. Section 5 provides a detailed description of the results of the analysis conducted, while Section 6 summarizes the key conclusions and offers a discussion.

3.2. LITERATURE REVIEW

Regulated carbon markets evolve in order to adapt to changing climate goals, varying in terms of reduction targets, permit allocation methods, and the sectors addressed. The first market created was the EU-ETS, which is the largest –covering the then 28 EU countries plus Iceland, Liechtenstein, and Norway– (Ellerman et al., 2010; Narassimhan et al., 2018). In terms of emissions volume, the standout is China's Carbon Market, which currently only covers the electricity sector. Other significant carbon markets include the Western Climate Initiative (WCI), which involves California and Quebec, the Regional Greenhouse Gas Initiative (RGGI), focused on the electricity sector and encompassing several states in the northeastern USA, South Korea's Carbon Market, New Zealand's Emissions Trading Scheme, Tokyo's Emissions Trading System, Mexico's Carbon Market, Kazakhstan's Emissions Trading System, the United Kingdom's Carbon Market, established post-Brexit to replace participation in the EU-ETS, the Provincial Systems of Canada, Switzerland's Emissions Trading System, and Emerging and

Developing Markets, which include countries that are developing their systems, such as Colombia, Chile, and Ukraine.

Since the beginning of the EU-ETS, interest in studying carbon markets from a financial perspective has been growing. Numerous studies have analyzed the connection between carbon and energy returns through volatility transmissions (Adekoya et al., 2021; Alkathery & Chaudhuri, 2021; Balcılar et al., 2016; Ji et al., 2018; Koch, 2014; Reboredo, 2014; Tan et al., 2020; Y. Wang & Guo, 2018; Wei & Lin, 2016; Zhang & Sun, 2016). Recent studies have focused on analyzing volatility transmissions between the carbon market and financial and commodity markets, applying the dynamic connectedness index by Diebold & Yilmaz (2009, 2012, 2014) alongside the decomposition of interdependence into frequency bands (Adekoya et al., 2021; Arif et al., 2021; Aslan & Posch, 2022; Baruník & Křehlík, 2018; Jiang & Chen, 2022; Meng et al., 2022; Suleman et al., 2023; Tiwari et al., 2022; X. Wang et al., 2022).

Adekoya et al. (2021) applied the dynamic connectedness index by Diebold & Yilmaz (2009, 2012, 2014) together with the decomposition of interdependence into frequency bands (Baruník & Křehlík, 2018) to examine the connectedness between the EU carbon market and various financial and commodity markets across different frequency ranges. Their key findings indicated that the transmission of volatility increased with higher frequencies, and that carbon was a net receiver except for copper. Additionally, uncertainty regarding US economic policies positively affected the transmission of volatility from carbon to the other markets.

Arif et al. (2021) analyzed the dynamics of connectedness between conventional and green investments in fixed income, equity, and energy markets, taking into account the effects of market uncertainty on connectedness dynamics through a subsample analysis during the COVID pandemic crisis. They applied the dynamic connectedness index of Diebold & Yilmaz (2012) to analyze connectedness between green and conventional financial markets for both the full sample and the COVID subsample. Additionally, they employed the method of Baruník & Křehlík (2018) to determine connectedness across short and long-term frequencies. According to their results for the full sample, the degree of connectedness between conventional and green investments was weak, with a more pronounced effect in the short term. Their time-varying analysis revealed peaks and troughs in connectedness between climate-conscious investments and conventional ones, suggesting that different global events, such as the Eurozone debt crisis (mainly between 2010 and 2012) and the sharp increase in oil and gas production in the USA triggered by new extraction techniques (from 2010 onwards) drove the association between alternative investments. Finally, they observed increased connectedness during the recent period of the COVID pandemic crisis.

Aslan & Posch (2022) analyzed the transmission of volatility from futures on ETS to nine sectoral indices of the FTSEurofirst300 during the third and fourth phases of the EU-ETS, employing the connectedness analysis (both static and dynamic) developed by Diebold & Yilmaz (2009, 2012, 2014). However, they did not investigate the short-term and long-term impact of a shock in one variable on others. According to their findings, carbon was a recipient of volatility, particularly from energy or energy-intensive sectors.

Jiang & Chen (2022) examined the static and dynamic connectedness between carbon markets, traditional energy (oil and coal), new energy (renewables, hydroelectric, and nuclear), and materials (iron, aluminum, cement, and plastic) based on the dynamic connectedness index by Diebold & Yilmaz (2012) and the method of Baruník & Křehlík (2018). According to their findings, total connectedness was greater in the short term, intensified after COVID-19, while the spillover effect from carbon markets was relatively small, mainly contributing to new energy. They observed that the spillover effect from

China's carbon markets after the COVID-19 outbreak was approximately double that of the pre-outbreak period. Finally, the time-varying analysis showed that both positive and negative connectedness values peaked in line with economic shocks.

Meng et al. (2022) applied the dynamic connectedness index developed by Diebold & Yilmaz (2012) together with the method proposed by Baruník & Křehlík (2018) to analyze the connectedness over time and at different frequencies –both short- and long-term– between EU carbon futures and the daily returns of ten publicly listed shipping companies (2016-2021), before and after the outbreak of COVID-19. According to their findings, volatility transmission intensified due to the trade war between China and the USA and the impact of COVID-19, with short-term transmission being higher and EU carbon futures acting as net receivers.

Suleman et al. (2023) used the dynamic connectedness analysis of Diebold & Yilmaz (2012, 2014) and also measured the extent to which shocks in the EU-ETS affected eight Dow Jones Sustainability Europe indices in both the short and long term (Baruník & Křehlík, 2018). Their main findings were that the carbon market was not highly connected to these eight indices, that it was a net receiver, and that most of the connectedness occurred in the short term (one day to five days).

Tiwari et al. (2022) analyzed the transmission of volatility between green bonds and renewable energy stocks, taking into account the carbon price (EU-ETS), for the period 2015-2020. They applied a dynamic connectedness approach based on TVP-VAR Diebold & Yilmaz (2009, 2012, 2014) and LASSO VAR. According to their findings, green bonds, solar energy, wind energy, and carbon price were net receivers of volatility, while clean energy was the largest net transmitter.

Wang et al. (2022) analyzed the dynamic correlations between clean energy, carbon, and green bonds, applying the DCC-MIDAS method, which combines the

GARCH model (Lee & Engel, 1999) and the DCC model (Engle, 2002). From their analysis, they concluded that clean energy, carbon, and green bonds were positively correlated, with the strongest correlations occurring between clean energy and green bonds. Like other studies, they found that shocks in financial markets influenced connectedness, which was particularly evident during the COVID-19 outbreak.

In sum, the evolution of regulated carbon markets reflects their adaptation to shifting climate goals, with varying reduction targets, permit allocation methods, and sectoral coverage. From the EU-ETS to emerging markets in Asia and the Americas, these systems have grown in both complexity and reach. The financial perspective on carbon markets has revealed significant volatility transmission between carbon, energy, financial, and commodity markets, particularly during periods of economic uncertainty. Using dynamic connectedness analysis methods, studies have consistently found that carbon markets often act as net receivers of volatility. These insights underscore the interconnectedness of carbon markets with broader financial systems and the critical need for strategic management to mitigate associated risks and enhance market stability.

3.2. METHODOLOGY

To analyze the transmission of return volatility from the EU-ETS to high- and low-emission companies during the third and fourth phases of the EU-ETS (2021-2030), we employ the dynamic connectedness measures proposed by Diebold and Yilmaz (2014) with a time-varying parameter (Antonakakis et al., 2020)[1], combined with the

[1] Antonakakis et al. (2020) add to the dynamic connectedness measures proposed by Diebold & Yılmaz (2014) a parameter for temporal variation by introducing a time-varying variance-covariance structure. Kalman filtering techniques are applied for parameter estimation, resulting in a model that is less sensitive to outliers and better adapted to potential changes.

decomposition of interdependence across frequency bands (Baruník & Křehlík, 2018), which is based on the spectral representation of the decomposition of the forecast error variance and allows us to measure the extent to which shocks in one variable at a given frequency (short or long term) influence other variables.

Based on this, our study specifically analyses how the logarithmic returns of the EU-ETS (derived from the prices of the EU Emissions Trading System, which represent carbon prices in this context) are interconnected with the returns of companies classified as high emitters and low emitters within the EU-ETS across different time frequencies. It examines how volatility shocks in the logarithmic returns of the EU-ETS propagate between high and low emission companies throughout the frequency spectrum. In other words, it provides empirical evidence that the relationships among these returns are not static; rather, shocks in the logarithmic returns of the EU-ETS transmit to the returns of high and low emission companies and vary across different time horizons: short-term or high frequency *versus* long-term or low frequency, identifying changes in the patterns of volatility transmission over time.

This methodological approach is particularly useful when working within the framework of the EU-ETS, where the relationships between the returns of the EU-ETS and the returns of high and low-emission companies can change rapidly due to political, economic, geopolitical, and technological factors. Furthermore, spectral connectedness information is helpful for enhancing the prediction of systemic risks and portfolio management.

To address dynamic connectedness (in the time domain), we present the TVP-VAR(p) model as (see Equations 1):

$$y_t = \Phi_t z_{t-1} + \epsilon_t, \qquad \epsilon_t | \Omega_{t-1} \sim N(0, \textstyle\sum_t) \tag{1}$$

where:

$$z_{t-1} = \begin{pmatrix} y_{t-1} \\ \vdots \\ y_{t-p} \end{pmatrix} \qquad \Phi_t' = \begin{pmatrix} \Phi_{1t} \\ \cdots \\ \Phi_{pt} \end{pmatrix} \tag{2}$$

where Ω_{t-1} represents all the information up to time t–1; y_t and ε_t are vectors of dimension $n \times 1$; z_{t-1} is a vector of dimension $np \times 1$; Φ_t and Φ_{it} are matrices representing the time varying VAR coefficients and have dimensions $n \times np$ and $n \times n$, respectively. Finally, the variance and covariance matrix $\sum_t$ has dimensions $n \times n$.

For simplicity, the TVP-VAR model can be rewritten as (see Equation 3):

$$\Phi(L)y_t = \varepsilon_t \tag{3}$$

where $\Phi(L) = I_N - \Phi_{1t}L - \cdots - \Phi_{pt}L^p$ and I_N is the identity matrix.

To implement the Kalman filter, Antonakakis et al. (2020) apply a series of damping factors $k_1,\ k_2$ ($k_1 = 0.99$ and $k_2 = 0.96$, according to Koop and Korobilis, 2014), which serve to adjust the influence of previous measurements and predictions on the current estimate. These factors are crucial for controlling the speed at which the filter responds to new measurements, particularly in environments where conditions may change over time, as is the case in our analysis (Welch & Bishop, 1995). Implementing the filter allows for the time-varying nature of the variance and covariance matrix and makes the model less sensitive to outliers.

Given the information at time *t*:

$$\epsilon_{t|t} = y_t - \Phi_{t|t}z_{t-1} \tag{4}$$

$$\Sigma_{t|t} = \kappa_1 \Sigma_{t-1|t-1} + (1-\kappa_2)\epsilon'_{t|t}\epsilon_{t|t}$$

For simplicity, the TVP-VAR model is transformed into a TVP- VMA(∞), moving average vector, based on the Wold representation theorem, and is rewritten as follows (see Equation 5):

$$y_t = \Psi(L)\varepsilon_t \tag{5}$$

where $\Psi(L)$ includes an infinite number of lags approximated by Ψ_h, calculated for h=1, …, H periods.

The coefficients Ψ_h are required to calculate the forecast error variance decomposition (GFEVD) (Koop et al., 1996; Pesaran & Shin, 1998), which illustrates the influence that variable *j* has on variable *i* in terms of its contribution to the variance of the prediction error. It is given by (see Equation 6):

$$\theta_{ijt}(H) = \frac{((\Sigma_t)_{jj}^{-1}\Sigma_{h=0}^{H}(\Psi_h\Sigma_t)_{ijt})^2}{\Sigma_{h=0}^{H}(\Psi_h\Sigma_t\Psi'_h)_{ii}} \tag{6}$$

Normalizing, it is obtained that (see Equation 7):

$$\tilde{\theta}_{ijt}(H) = \frac{\theta_{ijt}(H)}{\Sigma_{j=1}^{N}\theta_{ijt}(H)} \tag{7}$$

This represents the contribution of variable *j* to the variance of the prediction error of variable *i* over a horizon *H*. The denominator reflects the cumulative effect of shocks across all variables (*j=1, ..., N*) on *i*, while the numerator indicates the cumulative effect of the shock from the *j*-th variable on *i*.

From GFEVD, the net pairwise connectedness index, directional connectedness index, and total connectedness between variables are calculated through the Total Connectedness Index (TCI). We begin with the net pairwise connectedness of variables, defined as follows (see Equation 8):

$$NPDC_{ij}(H) = (\tilde{\theta}_{ijt}(H) - \tilde{\theta}_{jit}(H)) * 100 \tag{8}$$

If $NPDC_{ij}$(H) is greater (less) than 0, it indicates that variable *i* dominates (is dominated by) variable *j*. The total directional connectedness represents how variable *i* transmits a shock to the rest in a given period and is defined as (see Equation 9):

$$TO_{it}(H) = C =_{i\rightarrow j,t} (H) = \sum_{i=1,i\neq j}^{n} \tilde{\theta}_{ji,t}(H) * 100, \tag{9}$$

while the total directional connectedness index of others shows how much variable *i* receives from the shocks produced in the other variables over a given period: that is,

$$FROM_{it}(H) = C_{i\leftarrow j,t}(H) = \sum_{j=1,i\neq j}^{n} \tilde{\theta}_{ij,t}(H) * 100. \tag{10}$$

By subtracting the directional connectedness towards others and that received from others, we obtain the net directional connectedness, which measures the average impact of a shock on a specific variable over a given period (see Equation 11).

$$NET_{i,t}(H) = TO_{i,t}(H) - FROM_{i,t}(H). \tag{11}$$

Thus, if $NET_{i,t}$ is positive, it means that the shock to variable i has a greater influence on the rest than it receives, which allows us to refer to it as dominant.

Finally, the total connectedness index (TCI) measures the average impact that variable *i* has on all the others. It is defined as (see Equation 12):

$$TCI_t(H) = \frac{1}{n} * TO_{it}(H) = \frac{1}{n} * FROM_{it}(H). \tag{12}$$

Once the methodology to account for how the influence of a shock in EU-ETS returns changes over time concerning the returns of high and low-emission companies has been described, we analyze the interconnections between these variables across different frequencies. In other words, we assess whether this influence is greater, lesser, or equal in the short term compared to the long term. To do this, we focus on spectral connectedness, using the spectral representation of variance decompositions based on frequency responses to shocks. This concept was introduced by Baruník & Křehlík (2018) and Stiassny (1996), who employed it to define measures of connectedness across the frequency spectrum. Chatziantoniou et al. (2023) applied the methodology outlined by Baruník & Křehlík (2018) to analyze interconnections among the main oil markets, distinguishing between short- and long-term effects. Specifically, they observed high frequency or short term (five days) and low frequency or long term (from six to 100 days), noting that connectedness occurred in the short term for the majority of the period analyzed.

The development of connectedness measures that capture how the variance of one variable is explained by shocks in others at different frequencies is based on the spectral density function, which is defined for a variable y_t and a frequency ω as (see Equation 13).

$$S_y(\omega) = \sum_{h=-\infty}^{\infty} E(y_t y'_{t-h}) e^{-i\omega h} = \Psi\left(e^{-i\omega}\right) \Sigma \Psi'\left(e^{+i\omega}\right), \tag{13}$$

where $\Psi\left(e^{-i\omega}\right) = \sum_{h=0}^{\infty} e^{-i\omega h} \Psi_h$ is the frequency response function, and $i = \sqrt{-1}$. These connectedness measures are defined as (see Equation 14):

$$\theta_{ijt}(\omega) = \frac{((\Sigma_t)_{jj}^{-1} \sum_{h=0}^{\infty} (\Psi(e^{-i\omega h}) \Sigma_t)_{ijt})^2}{\sum_{h=0}^{\infty} (\Psi(e^{-i\omega h}) \Sigma_t \Psi(e^{+i\omega h}))_{ii}} \tag{14}$$

Normalizing, it is obtained that (see Equation 15):

$$\tilde{\theta}_{ijt}(\omega) = \frac{\theta_{ijt}(\omega)}{\sum_{j=1}^{N} \theta_{ijt}(\omega)}, \tag{15}$$

where $\tilde{\theta}_{ijt}(\omega)$ represents the part of the spectrum of variable i that at a given frequency ω is attributed to a shock in variable *j*. In our analysis –like Chatziantoniou et al. (2023)– we are interested in assessing connectedness in both the short and long term, rather than connectedness at a specific frequency. For this reason, frequencies are grouped within an interval $d = (a, b)$, such that, for that interval, the part of the spectrum of variable *i* attributed to a shock in variable *j* is given by (see Equation 16):

$$\tilde{\theta}_{ijt}(d) = \int_a^b \tilde{\theta}_{ijt}(\omega)\, d\omega. \tag{16}$$

From $\tilde{\theta}_{ijt}(d)$, we define the connectedness measures that take into account both short-term and long-term effects (see Equations 17):

$$NPDC_{ij}(d) = (\tilde{\theta}_{ijt}(d) - \tilde{\theta}_{jit}(d)) * 100.$$

$$TO_{it}(d) = C =_{i \to j,t} (d) = \sum_{i=1, i \neq j}^{n} \tilde{\theta}_{ji,t}(d) * 100.$$

$$FROM_{it}(d) = C_{i \leftarrow j,t}(d) = \sum_{j=1, i \neq j}^{n} \tilde{\theta}_{ij,t}(d) * 100. \quad (17)$$

$$NET_{i,t}(d) = TO_{i,t}(d) - FROM_{i,t}(d).$$

$$TCI_t(d) = \frac{1}{n} * TO_{it}(d) = \frac{1}{n} * FROM_{it}(d).$$

3.4. DATA

To study how shocks in EU-ETS returns are transmitted to the returns of high and low emission companies, examine how these transmissions vary in the short versus long term, and identify changes in the patterns of volatility transmission over time, we use daily data of returns of 32 companies belonging to STOXX Europe 600, for the period 01/01/2013-30/04/2024. Data are collected from Eikon DataStream. Of the 32 companies, 16 are classified as high-emission companies, with an annual mean of direct CO_2 equivalent emissions over revenues of 1404.52 tons, while the remaining 16 are low-emission companies, with an annual mean of 4.03 tons. It is important to note that many of the selected companies are currently implementing sustainability strategies to further reduce their carbon footprint. Decarbonization of companies requires significant investment in R&D as it relies on technological innovations.

In particular, as companies with high CO_2 emissions, we selected them by sector: (1) Energy and utilities: ENEL (Italy), RWE (Germany), and E.ON (Germany); (2) Oil and gas: Shell (Netherlands/UK), Repsol (Spain), Total (France), and BP (UK); (3) Mining and metals: ThyssenKrupp (Germany), ArcelorMittal (Luxembourg), and Rio Tinto (UK/Australia); (4) Cement and building materials: HeidelbergCement (Germany) and LafargeHolcim (Switzerland); (5) Aviation: Air France-KLM (France/Netherlands) and Lufthansa (Germany); and (6) Chemicals: Bayer (Germany) and BASF (Germany).

As companies with low CO_2 emissions from sectors with a lower carbon footprint because they do not directly rely on energy-intensive processes, we selected the following: (1) Technology and software: Amadeus IT Group (Spain), SAP (Germany), and ASML Holding (Netherlands); (2) Telecommunications: Telefónica (Spain), Orange (France), and Deutsche Telekom (Germany); (3) Finance and insurance: BNP Paribas (France), ING Group (Netherlands), and Allianz (Germany); (4) Health and pharmaceuticals: Sanofi (France), Novo Nordisk (Denmark), and Roche (Switzerland); (5) Consumer goods: Adidas (Germany), L'Oreal (France), and Unilever (UK/Netherlands); (6) Consulting services: Capgemini (France).

The study period encompasses the third (2013-2020) and fourth phases (2021-2030) of the EU ETS (from 2013 to 2024). More specifically, it was divided into three sub-periods: the first, from 01/01/2013 to 31/12/2017; the second, from 01/01/2018 to 30/10/2020; and the third, from 01/11/2020 to 30/04/2024. According to Wang and Guo (2018), the connectedness of EUAs with the prices of other assets is sensitive to extreme events, which is why we divided the total sample into three subsamples, taking into account relevant events in order to see whether the connectedness of the EU-ETS with the prices of high and low-emission companies is also affected. In particular, in 2018, there was a rise in CO_2 prices due to various reasons, primarily the coming into force of the reform of the EU Emissions Trading System, which included a reduction in the supply of emission permits following the approval of the Market Stability Reserve (European Parliament, 2018). Other contributing factors to the increase in carbon prices included the rise in energy demand driven by economic growth in Europe and extreme weather conditions in certain parts of Europe (frequent and intense heatwaves, prolonged drought periods, sudden and heavy rainfall episodes, etc.), together with the rise in natural gas prices relative to coal, which is more CO_2-intensive.

In 2020, the key event was the official withdrawal of the United States from the Paris Agreement on climate change on 4 November 2020. According to the President of the United States, this agreement imposed unnecessary financial and economic burdens on the country, negatively affecting the development of its energy industry and mainly benefitting China. However, on 19 February 2021, the United States again signed the Paris Agreement following Biden's coming into office as president.

3.5. RESULTS

Figure 1 shows the evolution of carbon prices (EU-ETS prices) throughout the whole analysis period, highlighting the impact of the key events mentioned. It is observed that prices remained stable until the end of 2017, after which an upward trend was noted, coinciding with the implementation of the European Union's Emissions Trading System reform. The launch of the Market Stability Reserve (MSR) contributed to the price increase. The primary objective of this mechanism was to prevent imbalances between the supply and demand of carbon emission allowances. It was established in 2018 and was launched in 2019 (European Parliament, 2018; Hintermayer, 2020). The MSR automatically adjusts the volume of allowances auctioned; if there is a surplus of allowances in circulation, some are withdrawn from the market and placed in reserve. Conversely, if there is a shortage, allowances are released from the reserve into the market. This trend was interrupted in 2020 due to the United States' withdrawal from the Paris Agreement.

Starting in 2021, the trend again shifted upwards, which was attributed to the initiation of the fourth phase of the EU-ETS (2021-2030), which reduces the annual emissions cap at a rate of 2.2% per year and aims for a 43% reduction in emissions by 2030 (European Commission, 2020), the United States rejoining the Paris Agreement, the rising demand for energy in Europe, and extreme weather conditions. In 2022, a significant drop in carbon prices was observed in the EU-ETS, primarily due to the impact of the war in Ukraine. This created uncertainty regarding economic growth in Europe, resulting in a reduction in emission allowances. Geopolitical instability led to increased volatility in financial markets, including the carbon market. From 2022 onwards, there was once again a rise in carbon prices driven by increased demand for ETS, as some countries temporarily turned to more polluting fuels in response to the energy crisis experienced in Europe due to the war in Ukraine.

Figure 1. Carbon prices (EU-ETS prices) from 2020-01-01 to 2024-04-30

The table of descriptive statistics (see Table 1) shows that the carbon mean return is high (0.102), surpassed only by the ASML Holding mean return (0.115). Regarding the variance of the carbon return series, it is noted to be the highest (21.317), reflecting greater volatility in the carbon market. This suggests that the market is uncertain and more susceptible to influences such as inaccuracies in climate policies or the effectiveness of regulations. Following closely in terms of volatility are companies from the mining and metals sectors, such as ArcelorMittal (9.826) and ThyssenKrupp (10.124), as well as those in aviation, like Air France-KLM (9.486).

Overall, most returns exhibit significant negative skewness, including the carbon return series, indicating a greater tendency to experience sharper declines than corresponding increases of a similar magnitude. All return series considered show excess kurtosis, indicating that their distributions have wider tails, and a more pronounced peak compared to the normal distribution. The Jarque-Bera statistic rejects the hypothesis of normality in all series, confirming the presence of skewness and leptokurtosis, as previously described. The ERS test (Elliott et al., 1996) rejects the hypothesis of non-stationarity in all cases. This test is a more powerful modification of the Augmented Dickey-Fuller (ADF) test. The Ljung-Box test –for both the return series and the squared returns– rejects the null hypothesis of independence, suggesting the presence of temporal dependence in both the conditional mean and variance for the return series and the majority of the series considered and their squares. Finally, in order to analyze the interaction or level of association between carbon returns and the returns of high and low emission companies, the non-parametric Kendall test (Kendall rank correlation test) is implemented. It is observed that the null hypothesis of no association between carbon returns and the returns of low emission companies is not rejected, except for Adidas and Capgemini. However, this does not mean that these companies are unaffected by the risks of climate change or related regulations. Conversely, as expected, this null hypothesis is rejected when testing the association of carbon returns with the returns of high emission companies.

Table 1. Descriptive statistics for daily returns

	Mean	Variance	Skew.	Kurtosis	ERS	p-value	Q(20)	p-value	Q2(20)	p-value	Kendall CO_2
CO_2	0.102	21.317	-0.761	15.348	-11.36***	(0.000)	193.34***	(0.000)	351.1***	(0.000)	1.000***
RWE	0.003	5.147	-0.561	7.307	-20.52***	(0.000)	10.421	(0.460)	134.5***	(0.000)	0.066***
E.ON	-0.002	3.126	-0.467	3.650	-19.27***	(0.000)	10.303	(0.473)	392.9***	(0.000)	0.037***
Enel	0.029	3.138	-1.081	13.190	-18.28***	(0.000)	23.100***	(0.004)	116.4***	(0.000)	0.022
TotalEnergies	0.025	3.48	-0.605	11.531	-16.90***	(0.000)	29.652***	(0.000)	685.6***	(0.000)	0.062***
BP	0.007	4.134	-0.181	13.448	-20.87***	(0.000)	49.623***	(0.000)	436.7***	(0.000)	0.052***
Shell	0.013	3.761	-0.416	13.160	-18.44***	(0.000)	44.515***	(0.000)	675.0***	(0.000)	0.045***
Repsol	-0.003	4.706	-0.468	10.378	-20.21***	(0.000)	32.700***	(0.000)	337.6***	(0.000)	0.050***
ArcelorMittal	-0.031	9.826	-0.388	5.362	-19.98***	(0.000)	16.425*	(0.073)	504.5***	(0.000)	0.029**
Thyssen	-0.058	10.124	0.742	15.924	-16.26***	(0.000)	18.676**	(0.030)	68.92***	(0.000)	0.053***
RioTinto	0.018	4.785	0.047	3.347	-16.50***	(0.000)	19.725**	(0.019)	235.7***	(0.000)	0.032**
Holcim	0.008	3.273	-0.399	6.372	-19.24***	(0.000)	27.635***	(0.000)	284.7***	(0.000)	0.056***
Heidelberg	0.031	3.92	-0.483	6.274	-13.29***	(0.000)	23.186***	(0.004)	721.4***	(0.000)	0.031**
Lufthansa	-0.020	6.791	0.124	7.026	-10.11***	(0.000)	13.887	(0.176)	115.7***	(0.000)	0.054***
AirFrance	-0.060	9.486	-0.109	5.880	-11.14***	(0.000)	17.913**	(0.041)	100.7***	(0.000)	0.044***
BASF	-0.016	3.528	-0.236	6.574	-15.96***	(0.000)	19.272**	(0.023)	113.1***	(0.000)	0.040***
Bayer	-0.041	4.075	-0.932	10.613	-18.17***	(0.000)	14.378	(0.150)	16.922*	(0.060)	0.034**

SAP	0.045	2.678	-1.458	26.305	-16.72***	(0.000)	17.625**	(0.046)	6.111	(0.895)	0.039***
ASML	0.115	5.348	0.059	4.182	-15.62***	(0.000)	18.089**	(0.038)	242.7***	(0.000)	-0.007
Amadeus	0.050	3.765	-0.126	10.183	-8.25***	(0.000)	13.412	(0.205)	312.5***	(0.000)	0.067***
Deutsche	0.039	2.152	-0.352	5.382	-14.60***	(0.000)	17.306*	(0.052)	208.7***	(0.000)	0.035**
Telefónica	-0.048	3.774	-0.423	11.444	-19.29***	(0.000)	11.390	(0.364)	163.1***	(0.000)	0.032**
Orange	0.001	2.596	-0.053	5.917	-19.14***	(0.000)	17.400**	(0.050)	198.7***	(0.000)	0.016
Allianz	0.039	2.665	-0.431	13.365	-15.95***	(0.000)	26.423***	(0.001)	466.3***	(0.000)	0.069***
ING	0.029	5.463	-0.460	9.505	-11.85***	(0.000)	26.954***	(0.001)	427.5***	(0.000)	0.054***
BNP	0.017	4.986	-0.532	7.934	-14.65***	(0.000)	18.637**	(0.031)	287.2***	(0.000)	0.054***
Novo	0.088	3.365	-0.416	9.340	-14.05***	(0.000)	24.179***	(0.003)	16.566*	(0.069)	-0.001
Sanofi	0.010	2.513	-1.407	17.225	-17.20***	(0.000)	17.405**	(0.050)	8.486	(0.673)	0.020
Roche	0.007	1.756	-0.263	4.585	-8.63***	(0.000)	14.593	(0.140)	111.8***	(0.000)	-0.004
Unilever	0.023	1.882	0.230	9.408	-15.54***	(0.000)	17.831**	(0.042)	101.8***	(0.000)	0.022
Loreal	0.062	2.29	0.036	3.606	-20.58***	(0.000)	26.699***	(0.001)	201.2***	(0.000)	0.022
Adidas	0.054	4.654	0.254	9.640	-21.29***	(0.000)	7.192	(0.806)	32.93***	(0.000)	0.033**
Capgemini	0.079	3.71	-0.164	4.845	-11.15***	(0.000)	10.860	(0.415)	466.3***	(0.000)	0.034**

Note: The ERS test is a powerful modification of the Augmented Dickey-Fuller (ADF) test. ERS tests a null hypothesis of a unit root (non-stationarity of the series); Q (20) is the Ljung–Box statistic for the returns which tests a null hypothesis that autocorrelations up to lag 20 equal zero. Q2 (20) is the Ljung–Box statistic for the squared returns which tests a null hypothesis that autocorrelations up to lag 20 equal zero.

*, ** and *** indicate the rejection of the null hypothesis of associated statistical tests at the 10%, 5% and 1% levels, respectively.

Below, we describe the extent to which the volatility of carbon returns during the period from 2013 to 2024 has a transmission effect on returns of European companies with high and low carbon emissions, the direction of this transmission, whether it changed during the study period, whether it is greater in the short term than in the long term, and finally, whether there are differences in this effect depending on whether companies have high or low emissions.

Tables 2, 3, and 4 illustrate the total static connectedness between the carbon market and the overall sample of companies across the three sub-periods considered. The total connectedness transmitted is shown in the "TO" row, while the received connectedness is displayed in the "FROM" row. The "NET" row indicates the net connectedness, yielding a negative value if it is a net transmitter and a positive value if it is a net receiver. "TCI" represents the total connectedness index, reflecting the overall degree of connectedness within the system. It is noted that the total connectedness index is very high and remains constant across the three periods: 81.4% from 01/01/2013 to 31/12/2017; 77.7% from 01/01/2018 to 30/10/2020; and 75.15% from 02/11/2020 to 30/04/2024.

As regards how carbon transmits a shock to other variables during the first period, Table 2 indicates that the total directional connectedness of carbon is 14.79%. Although this is the lowest value among all entries in the "TO" row, it is not regarded as low and is primarily attributed to uncertainty surrounding the implementation of stricter future climate policies, following the adoption of the Paris Agreement in 2015 and the introduction of the Market Stability Reserve, also in 2015. This finding is consistent with results obtained by Aslan & Posch (2022) and Suleman et al. (2023).

Table 2. Static volatility connectedness matrix of "Carbon-High-Low emission firms" system (until 2018)

	ALL			SHORT			LONG		
	TO	FROM	NET	TO	FROM	NET	TO	FROM	NET
CO_2	14.79	48.66	-33.87	11.89	41.36	-29.46	2.90	7.30	-4.40
RWE	70.83	80.04	-9.21	57.54	62.34	-4.80	13.29	17.70	-4.41
E.ON	84.01	82.12	1.89	70.13	65.11	5.01	13.89	17.01	-3.12
Enel	98.91	86.27	12.64	81.52	72.95	8.57	17.40	13.33	4.07
TotalEnergies	113.4	87.99	25.47	93.12	71.38	21.74	20.34	16.61	3.73
BP	74.30	81.21	-6.91	62.48	64.32	-1.84	11.82	16.89	-5.08
Shell	73.30	81.32	-8.03	59.57	64.16	-4.58	13.72	17.17	-3.45
Repsol	103.3	86.92	16.42	83.49	70.54	12.95	19.85	16.38	3.47
ArcelorMittal	61.25	77.78	-16.53	48.93	63.53	-14.61	12.32	14.24	-1.92
Thyssen	83.73	83.70	0.02	67.09	66.10	0.98	16.64	17.60	-0.96
RioTinto	56.81	76.15	-19.34	45.15	63.14	-17.99	11.65	13.00	-1.35
Holcim	90.36	84.17	6.19	72.20	65.33	6.87	18.15	18.84	-0.69
Heidelberg	95.10	85.56	9.54	78.86	69.90	8.97	16.24	15.66	0.58
Lufthansa	66.07	78.74	-12.67	56.52	62.13	-5.61	9.55	16.61	-7.06
AirFrance	60.89	77.96	-17.06	49.40	61.46	-12.06	11.49	16.49	-5.00
BASF	112.4	87.76	24.69	91.83	70.64	21.18	20.63	17.12	3.51
Bayer	99.07	86.19	12.88	82.07	71.02	11.05	16.99	15.17	1.83
SAP	97.61	86.23	11.37	77.94	67.20	10.74	19.67	19.04	0.63
ASML	56.54	75.06	-18.52	44.07	59.25	-15.18	12.47	15.81	-3.34
Amadeus	67.93	80.74	-12.81	54.63	62.12	-7.49	13.30	18.62	-5.32
Deutsche	90.11	84.57	5.54	72.37	67.74	4.63	17.74	16.83	0.91
Telefónica	88.94	83.90	5.04	68.99	67.46	1.53	19.95	16.44	3.51
Orange	73.97	81.10	-7.12	56.97	67.20	-10.23	17.00	13.90	3.10
Allianz	116.1	88.36	27.82	92.07	72.08	20.00	24.10	16.28	7.82
ING	107.0	87.29	19.72	87.45	72.53	14.93	19.55	14.76	4.79
BNP	114.7	87.90	26.80	94.48	74.05	20.43	20.21	13.85	6.36
Novo	40.04	65.44	-25.40	32.58	53.48	-20.90	7.46	11.96	-4.50
Sanofi	85.91	83.40	2.50	71.70	70.07	1.63	14.21	13.33	0.88
Roche	76.22	81.58	-5.35	61.70	66.86	-5.16	14.53	14.72	-0.20
Unilever	69.44	79.58	-10.14	55.96	65.48	-9.52	13.48	14.10	-0.62
Loreal	90.70	84.92	5.78	74.51	73.28	1.23	16.19	11.64	4.55
Adidas	68.54	79.68	-11.14	51.90	65.14	-13.24	16.64	14.54	2.10
Capgemini	83.69	83.90	-0.20	67.95	67.72	0.23	15.75	16.18	-0.43
TCI		81,4%			65,97%			15,43%	

Note: Tables 2 illustrates the total static connectedness between the carbon market and the overall sample of companies from 2013 to 2018. The total connectedness transmitted is shown in the TO column, while received connectedness is displayed in the FROM column. The NET column indicates the net connectedness, yielding a negative value if it is a net transmitter and a positive value if it is a net receiver. TCI represents the total connectedness index.

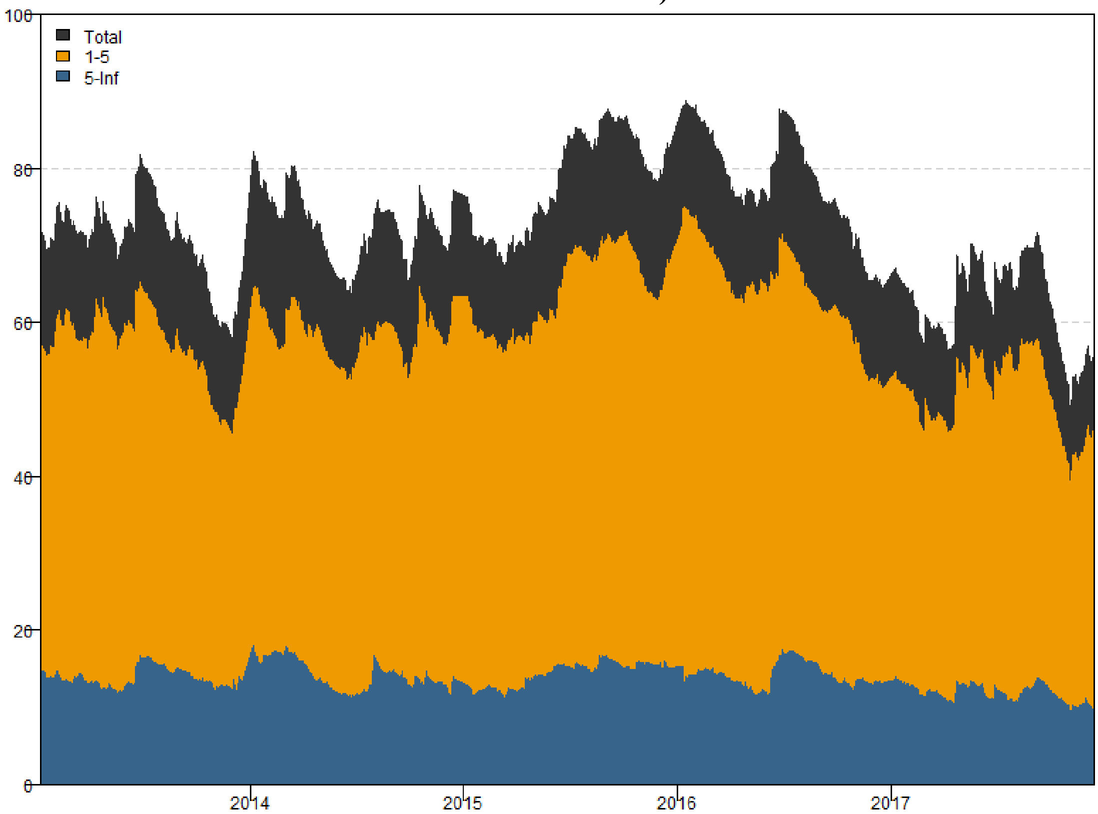
The main net transmitters are TotalEnergy (25.47%), Repsol (16.42%), BASF (24.69%), Allianz (27.82%), ING (19.72%), and BNP (26.80%), belonging to the energy, chemical and finance and insurance sectors. This is due to fluctuations in energy prices (changes in oil and natural gas prices) and uncertainty in the markets caused by Brexit, including the carbon market, as the UK was a relevant country in the EU -ETS.

Regarding directional connectedness 'FROM', most assets receive around 80%. The lowest connectedness received from other assets is for carbon, which receives 48.66%. Calculating the difference between the connectedness received and transmitted by carbon, it is observed that, on average, carbon is a net receiver (-33.87%) in this sub-period.

If we consider the frequency (short and long term), it is observed that most of the connectedness occurs in the short term, 65.97%, while in the long term it is 15.43%. As for carbon, it transmits 11.89% in the short term and 2.90% in the long term.

Figure 2 shows the temporal dynamics of the total system connectedness (surface in black) between 01/01/2013 and 31/12/2017, also measured in frequency bands. Dynamic connectedness is calculated from the prediction error variance decomposition (FEVD), using a 200-day rolling window and a 100-day time horizon. The orange shaded area shows short-term connectedness (one day-five days) and corresponds to transmissions up to five days (one week). The blue area reflects long-term connectedness (five days- infinity days). Total connectedness is seen to vary between approximately 50% and 85% throughout the first sub-period. It peaks, coinciding with relevant events such as an oversupply of emission permits in 2013, the adoption of the Paris Agreement in December 2015 (Fahmy, 2022) and in June 2016 with Brexit. In terms of frequency, most of the connectedness occurs in the short term.

Figure 2. Dynamic total connectedness throughout the first sub-period (January 2013 – December 2017)



Note: Figure 2 presents the time-frequency dynamics of total connectedness between EU-ETS returns and the rest of the variables over the first sub-period. The black area indicates the time dynamic connectedness values while the orange and blue areas illustrate the short- and long-term frequency connectedness, respectively.

Table 3 shows that the total directional carbon connectedness between 01/01/2018 and 30/10/2020 is higher than in the previous sub-period, and is specifically equal to 20.15%. This increase is due to the beginning of the implementation of the EU-ETS reforms –in particular, the approval in 2018 of the Market Stability Reserve (MSR) to address the oversupply of allowances and its implementation in 2019. As in the previous sub-period, the main net transmitters are companies belonging to the energy (TotalEnergy, 19.68%), mining and metals (ArcelorMittal, 13.35%) sectors, companies in the cement and building materials sector (LafargeHolcim, 28.95%, and Heidelberg, 15.59%), the chemicals sector (BASF, 28.74%) and the finance and insurance sector (Allianz, 29.87%, ING, 17.25%, and BNP, 15.69%). This is attributed to market uncertainty triggered by the global recession and political uncertainties such as Brexit, fluctuations in energy demand (especially aggravated in 2020 with the COVID 19 pandemic, which also negatively affected the construction sector and significantly reduced its activity). In particular, between 2018 and 2021, the carbon price in the EU-ETS made the use of natural gas more cost-effective than coal, allowing for a 30% reduction in carbon intensity in the power sector (X. Wang et al., 2022). Furthermore, in 2020, the United States withdrew from the Paris Agreement.

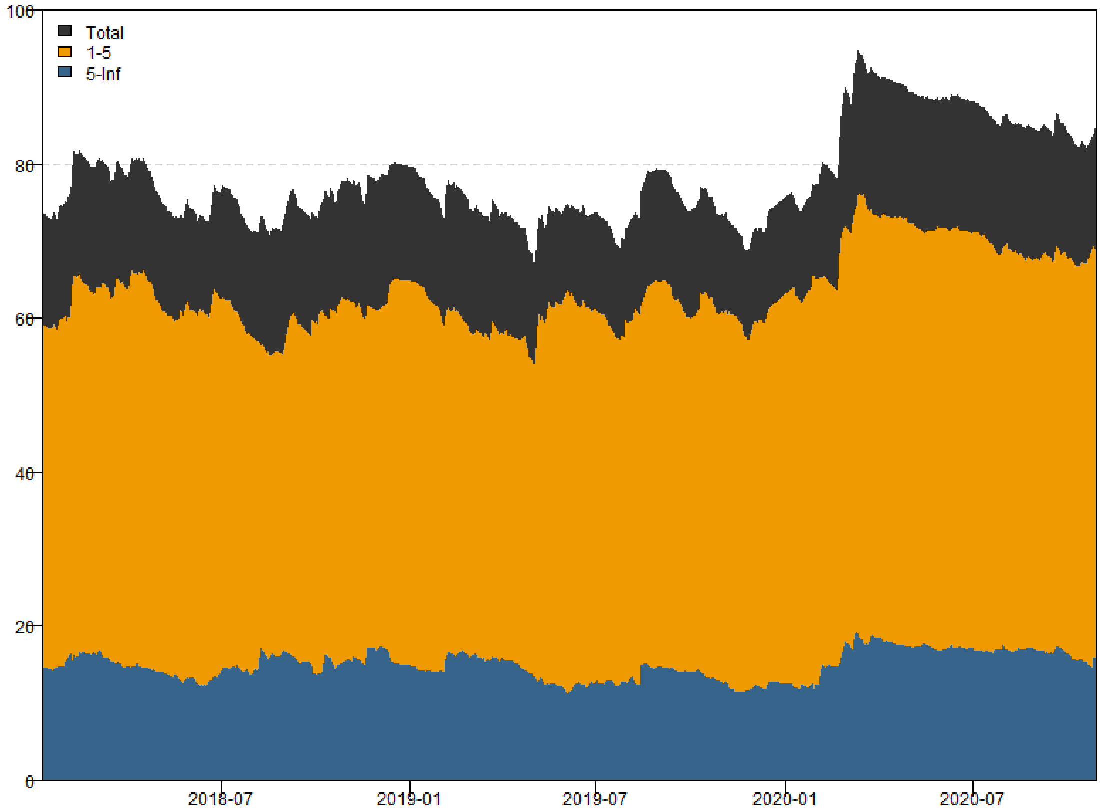
Table 3. Static volatility connectedness matrix of "Carbon-High-Low emission firms" system (From 2018-To 2020)

	ALL			SHORT			LONG		
	TO	FROM	NET	TO	FROM	NET	TO	FROM	NET
CO_2	20.15	47.60	-27.44	16.75	37.11	-20.36	3.41	10.49	-7.08
RWE	59.11	72.62	-13.50	48.14	57.83	-9.69	10.98	14.79	-3.81
E.ON	61.42	72.99	-11.57	47.27	59.27	-12.00	14.15	13.72	0.42
Enel	72.23	76.64	-4.41	59.98	63.65	-3.67	12.25	12.99	-0.74
TotalEnergies	104.5	84.85	19.68	84.38	68.13	16.25	20.15	16.73	3.42
BP	86.03	80.94	5.09	67.66	67.81	-0.15	18.37	13.13	5.24
Shell	87.20	81.86	5.34	70.01	65.97	4.04	17.18	15.89	1.30
Repsol	93.23	83.39	9.84	76.16	66.34	9.83	17.07	17.05	0.02
ArcelorMittal	95.33	81.98	13.35	75.30	67.80	7.50	20.03	14.18	5.85
Thyssen	69.90	77.95	-8.05	57.28	62.40	-5.13	12.63	15.55	-2.92
RioTinto	75.10	78.92	-3.82	59.43	67.60	-8.18	15.67	11.31	4.36
Holcim	115.0	86.05	28.95	92.88	68.31	24.57	22.12	17.74	4.38
Heidelberg	99.62	84.03	15.59	78.75	68.32	10.44	20.87	15.71	5.15
Lufthansa	63.01	74.42	-11.41	52.83	60.76	-7.94	10.18	13.65	-3.47
AirFrance	54.29	69.73	-15.45	43.67	55.36	-11.69	10.61	14.37	-3.76
BASF	114.7	86.09	28.66	93.75	67.82	25.92	21.01	18.27	2.74
Bayer	81.95	80.28	1.67	66.54	61.73	4.81	15.41	18.55	-3.14
SAP	90.19	81.51	8.68	73.96	68.08	5.88	16.23	13.43	2.80
ASML	71.43	76.44	-5.01	58.68	63.89	-5.21	12.75	12.55	0.20
Amadeus	83.02	80.74	2.28	68.67	62.51	6.16	14.35	18.23	-3.88
Deutsche	72.04	77.90	-5.86	57.91	60.78	-2.87	14.13	17.12	-2.98
Telefónica	79.17	79.22	-0.04	61.18	63.76	-2.58	17.99	15.46	2.53
Orange	65.21	73.14	-7.93	51.72	57.29	-5.58	13.49	15.85	-2.36
Allianz	116.1	86.14	29.87	93.57	69.72	23.86	22.44	16.42	6.02
ING	101.5	84.31	17.25	83.32	66.54	16.78	18.24	17.77	0.47
BNP	100	84.34	15.69	83.88	65.61	18.27	16.15	18.73	-2.59
Novo	44.49	65.29	-20.79	33.60	54.84	-21.24	10.89	10.45	0.45
Sanofi	63.91	75.26	-11.36	52.98	59.38	-6.40	10.92	15.88	-4.96
Roche	60.79	74.59	-13.81	48.91	62.50	-13.58	11.87	12.09	-0.22
Unilever	51.44	71.34	-19.90	42.66	55.93	-13.26	8.78	15.41	-6.64
Loreal	86.81	80.53	6.29	69.52	63.02	6.50	17.30	17.51	-0.21
Adidas	56.77	75.24	-18.47	46.48	67.16	-20.68	10.29	8.08	2.21
Capgemini	68.24	77.65	-9.40	54.23	64.85	-10.62	14.02	12.80	1.21
TCI		77.70%			62.79%			14.91%	

Note: Tables 3 illustrates the total static connectedness between the carbon market and the overall sample of companies from 2018 to 2020. The total connectedness transmitted is shown in the TO column, while received connectedness is displayed in the FROM column. The NET column indicates the net connectedness, yielding a negative value if it is a net transmitter and a positive value if it is a net receiver. TCI represents the total connectedness index.

Directional connectedness remains similar to the previous sub-period. Most assets receive around 80% and carbon 47.6%, which remains a net receiver (-27.44%). As expected, most connectedness occurs in the short term –62.79%– while the long term is 14.91%. As for carbon, it transmits 16.75% in the short term and 3.41% in the long term.

Figure 3. Dynamic total connectedness throughout the second sub-period (January 2018 – October 2020)



Note: Figure 3 presents the time-frequency dynamics of total connectedness between EU-ETS returns and the rest of the variables over the second sub-period. The black area indicates the time dynamic connectedness values while the orange and blue areas illustrate the short- and long-term frequency connectedness, respectively.

The temporal dynamics of the total connectedness of the system (area in black) 01/01/2018 and 30/10/2020 is illustrated in Figure 3. As can be seen in figure 3, the temporal evolution of connectedness is more stable in this sub-period than in the previous one, oscillating between 75% and 90% approximately. The highest peak occurs in 2020, the year in which two very relevant events took place; the onset of the COVID 19 pandemic and the USA's withdrawal from the Paris Pact. As in the previous sub-period, most connectedness occurs in the short term.

Total directional carbon connectedness has continued to increase compared to the previous sub-periods. As Table 4 shows, in the third sub-period (between 02/11/2020 and 30/04/2024) it is equal to 28.41%, compared to 20.15% in the second sub-period (01/01/2018 and 30/10/2020) and 14.79% in the first sub-period (between 01/01/2013 and 31/12/2017). It has approximately doubled over the eleven years. This persistent increase in carbon volatility transmission has been due to the implementation of the EU-ETS reforms to accelerate decarbonization and meet the EU's climate targets. On 22 June 2022, the European Parliament voted to accept amendments to a major legislative climate action package (i.e., Fit for 55) proposed by the European Commission in July 2021, whose main objective is to reduce emissions by 57% in the sectors covered by the EU-ETS by 2030, up from the previous target of 43% in 2005. The number of allowances available for free to industry to cover annual emissions is decreasing every year, with the purchase of allowances being promoted through auctioning, which increases the cost of emissions, to achieve overall emissions reduction. Moreover, until now, decarbonization of the electricity sector has been sufficient to achieve the emission reduction targets of the EU-ETS. However, it is now necessary to increase the scope and to include more sectors and gases (X. Wang et al., 2022).

Table 4. Static volatility connectedness matrix of "Carbon-High-Low emission firms" system (From 2020-To 2024)

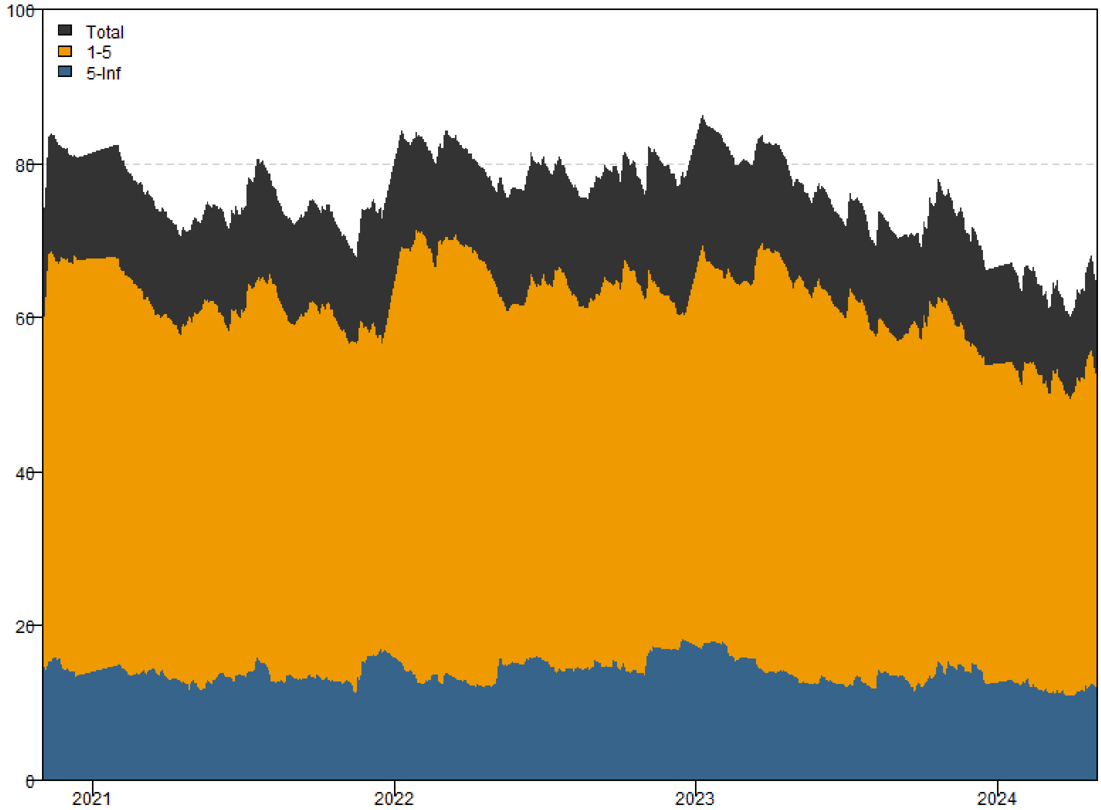
	ALL			SHORT			LONG		
	TO	FROM	NET	TO	FROM	NET	TO	FROM	NET
CO_2	28.41	54.72	-26.31	23.61	44.52	-20.90	4.80	10.21	-5.41
RWE	52.68	67.25	-14.56	42.05	54.26	-12.21	10.63	12.98	-2.35
E.ON	57.94	68.34	-10.39	48.51	54.35	-5.84	9.43	13.99	-4.56
Enel	87.85	78.78	9.07	71.29	65.64	5.65	16.55	13.14	3.42
TotalEnergies	102.3	84.40	17.94	82.37	70.16	12.21	19.96	14.24	5.73
BP	94.11	83.18	10.94	79.00	69.64	9.36	15.11	13.54	1.57
Shell	93.63	83.62	10.00	76.47	69.95	6.52	17.15	13.67	3.48
Repsol	88.03	82.36	5.66	70.79	67.38	3.41	17.23	14.98	2.25
ArcelorMittal	85.36	79.50	5.86	66.91	65.61	1.30	18.45	13.89	4.55
Thyssen	77.82	79.17	-1.35	62.88	62.89	-0.01	14.94	16.27	-1.33
RioTinto	63.66	75.26	-11.61	51.07	61.51	-10.44	12.59	13.76	-1.16
Holcim	105.6	84.31	21.37	86.87	69.14	17.73	18.80	15.17	3.64
Heidelberg	92.46	81.88	10.58	76.16	67.99	8.17	16.30	13.89	2.41
Lufthansa	85.85	81.58	4.26	70.62	66.59	4.03	15.22	14.99	0.23
AirFrance	84.58	80.78	3.79	68.42	65.54	2.88	16.16	15.24	0.91
BASF	108.1	84.49	23.58	87.88	69.49	18.39	20.20	15.01	5.19
Bayer	65.23	73.53	-8.30	52.45	62.51	-10.05	12.78	11.02	1.76
SAP	67.41	73.06	-5.65	53.44	57.97	-4.53	13.97	15.09	-1.12
ASML	63.82	71.97	-8.14	50.36	58.37	-8.01	13.46	13.59	-0.13
Amadeus	79.82	79.82	0.00	63.14	66.49	-3.35	16.68	13.33	3.35
Deutsche	67.21	72.63	-5.43	55.25	59.13	-3.88	11.95	13.50	-1.55
Telefónica	71.25	76.55	-5.30	60.65	60.20	0.45	10.59	16.35	-5.76
Orange	55.28	69.69	-14.41	45.67	56.36	-10.69	9.61	13.33	-3.72
Allianz	105.3	83.68	21.65	85.04	69.40	15.64	20.29	14.28	6.01
ING	104.9	84.38	20.61	90.08	68.18	21.90	14.91	16.20	-1.29
BNP	117.6	86.07	31.60	100.6	70.08	30.60	16.99	15.99	1.00
Novo	37.62	56.59	-18.98	30.93	42.77	-11.84	6.69	13.82	-7.13
Sanofi	48.91	61.35	-12.45	40.65	50.04	-9.39	8.26	11.31	-3.05
Roche	38.40	58.88	-20.48	31.29	45.99	-14.70	7.10	12.89	-5.78
Unilever	32.23	55.06	-22.82	26.24	46.10	-19.87	6.00	8.95	-2.96
Loreal	72.97	74.87	-1.90	59.08	64.37	-5.30	13.89	10.50	3.39
Adidas	67.87	76.07	-8.19	55.93	63.42	-7.50	11.95	12.64	-0.70
Capgemini	75.42	76.06	-0.64	62.14	61.88	0.26	13.28	14.18	-0.90
TCI		75,15%			61,45%			13,70%	

Note: Tables 4 illustrates the total static connectedness between the carbon market and the overall sample of companies from 2020 to 2024. The total connectedness transmitted is shown in the TO column, while received connectedness is displayed in the FROM column. The NET column indicates the net connectedness, yielding a negative value if it is a net transmitter and a positive value if it is a net receiver. TCI represents the total connectedness index.

Directional connectedness 'FROM' remains stable throughout the period. Also in the third sub-period, most of the assets receive around 80% and carbon 54.72%, being a net receiver (-26.31%). As regards frequency, as in the previous two sub-periods, most connectedness occurs in the short term; specifically, 61.45%, while in the long term it is 13.7%. In the short term, carbon transmits 23.61% and in the long term, 4.8%. The largest net transmitters of volatility in this sub-period are Total (17.94%), BP (10.94%), Shell (10%), LafargeHolcim (21.37%), Heidelberg (10,58%), BASF (23.58%), Allianz (21.65%), ING (20.61%) and BNP (31.6%). Carbon appears as the largest net recipient (-26.31%) followed by Unilever (-22.82%) and Roche (-20.48%), from the health and pharmaceuticals sector.

Figure 4 shows the temporal dynamics of the total connectedness of the system (area in black) for the sub-period 02/11/2020 and 30/04/2024. This figure shows that the temporal evolution of connectedness is stable, as in the second sub-period, although it decreases slightly from mid-2023 onwards. It ranges between approximately 65% and 85%. The highest values occur during 2020, as a consequence of the amendments to the Fit for 55 package.

Figure 4. Dynamic total connectedness throughout the third sub-period (November 2020 – April 2024)



Note: Figure 4 presents the time-frequency dynamics of total connectedness between EU-ETS returns and the rest of the variables over the third sub-period. The black area indicates the time dynamic connectedness values while the orange and blue areas illustrate the short- and long-term frequency connectedness, respectively.

Table 5. Evolution of the transmission of volatility from carbon to firms by frequency and sub-periods

	ALL			SHORT			LONG		
	2018	18-20	20-24	2018	18-20	20-24	2018	18-20	20-24
RWE	0.95	0.51	2.01	0.67	0.41	1.53	0.27	0.10	0.48
E.ON	0.64	0.65	1.40	0.49	0.54	1.14	0.14	0.11	0.26
Enel	0.29	0.95	0.48	0.23	0.81	0.40	0.05	0.14	0.08
TotalEnergies	0.30	0.37	0.66	0.25	0.31	0.58	0.06	0.07	0.08
BP	0.45	0.40	0.81	0.37	0.34	0.73	0.08	0.06	0.09
Shell	0.48	0.45	0.63	0.38	0.38	0.55	0.10	0.07	0.08
Repsol	0.44	0.44	0.67	0.35	0.36	0.60	0.09	0.07	0.07
ArcelorMittal	0.46	0.69	0.71	0.39	0.55	0.56	0.07	0.13	0.15
Thyssen	0.30	0.63	1.11	0.23	0.50	0.90	0.07	0.13	0.21
RioTinto	0.64	0.50	0.89	0.52	0.44	0.70	0.12	0.06	0.19
Holcim	0.44	0.60	0.72	0.35	0.46	0.62	0.09	0.14	0.10
Heidelberg	0.24	0.81	0.57	0.20	0.69	0.50	0.03	0.12	0.06
Lufthansa	0.38	1.11	0.82	0.30	0.96	0.71	0.08	0.15	0.12
AirFrance	0.44	1.51	0.73	0.35	1.27	0.61	0.09	0.24	0.12
BASF	0.28	0.38	0.74	0.23	0.30	0.66	0.05	0.08	0.08
Bayer	0.36	0.42	1.10	0.30	0.31	0.92	0.06	0.12	0.17
SAP	0.31	0.74	1.01	0.25	0.62	0.77	0.06	0.12	0.24
ASML	1.00	0.79	0.80	0.77	0.71	0.65	0.23	0.08	0.15
Amadeus	0.55	0.94	0.79	0.46	0.75	0.71	0.09	0.18	0.08
Deutsche	0.35	0.48	0.77	0.28	0.36	0.61	0.08	0.12	0.15
Telefónica	0.37	0.59	0.66	0.29	0.52	0.54	0.08	0.07	0.12
Orange	0.33	0.66	0.69	0.27	0.57	0.58	0.05	0.09	0.12
Allianz	0.32	0.40	0.56	0.26	0.32	0.48	0.07	0.08	0.08
ING	0.33	0.54	0.66	0.27	0.42	0.55	0.06	0.12	0.11
BNP	0.28	0.46	0.55	0.23	0.38	0.48	0.04	0.08	0.07
Novo	0.66	0.70	2.08	0.55	0.60	1.69	0.11	0.09	0.39
Sanofi	0.38	0.44	0.97	0.31	0.36	0.85	0.07	0.08	0.12
Roche	0.66	0.57	1.78	0.55	0.45	1.57	0.10	0.12	0.20
Unilever	0.62	0.66	0.92	0.49	0.54	0.72	0.13	0.13	0.20
Loreal	0.35	0.38	0.76	0.29	0.31	0.62	0.06	0.06	0.14
Adidas	0.62	0.81	0.70	0.52	0.72	0.59	0.10	0.10	0.11
Capgemini	0.57	0.57	0.67	0.47	0.48	0.51	0.10	0.09	0.16

Note: Table 5 shows the evolution of the transmission of carbon volatility to the returns of the companies in the sample over the three sub-periods: from 2013 to 2018, from 2018 to 2020, and from 2020 to 2024. The total connectedness transmitted is shown in the ALL column, while the transmission in the short term and long term are in the SHORT and LONG columns, respectively.

Table 5 reports the evolution of the transmission of carbon volatility to the returns of the companies in the sample over the three sub-periods. As can be seen in this table, in all cases except for ASML Holding, which belongs to the technology and software sector (a low-emission company), the transmission of carbon volatility to the returns of the companies in the sample has increased at the end of the period considered and the greatest transmission has always been in the short term. The largest increase in carbon volatility transmission (ALL column) is to energy intensive companies' returns: RWE (2.01%), E.ON (1.4%), ThysenKrupp (1.11%); and to healthcare and pharmaceutical companies: Bayer (1.1%), SAP (1.01%), Novo (2.08%), and Roche (1.78%). The largest net transmitters of volatility in this sub-period are Total (17.56%), BP (10.52%), LafargeHolcim (21.46%), Heidelberg (11.06%), BASF (23.31%), Allianz (22.1%), ING (20.08%), and BNP (32.07%). Carbon appears as the largest net recipient (26.52%) followed by Roche (20.85%) and Unilever (22.86%), from the health and pharmaceuticals sector.

To conclude our analysis, we split the sample into high emitting and low emitting firms to study whether the shocks to EU-ETS returns are transmitted equally or differently depending on whether the firm is classified as high or low emitting. Table 6 offers the results for the three sub-periods considered and shows that the total connectedness index (TCI) is high and similar in the three sub-periods and for the two subsamples considered, although it is lower than that obtained for the total sample (see Table 2,3 and 4). For the subsample of high-emission companies, the figures are 66.4%, 63.3%, and 63.8% for each of the three sub-periods, respectively, while for the sub-sample of low-emission companies they are 72.1%, 66.6% and 61.1%, respectively. As for the volatility transmission of carbon, it is seen to increase over the period for both subsamples; from

9.82% to 17.83% for the subsample of high-emitting companies, and from 11.96% to 21.71% for the subsample of low-emitting companies. The evolution and values are similar for the two subsamples, and it is expected to increase over the eleven years, due to the implementation of the EU-ETS reforms. It is slightly (but not significantly) higher in the sub-sample of low-emitting companies, which is due to the fact that this sub-sample includes companies in the finance sector, whose volatility is affected by uncertainty in financial markets due to the implementation of EU-ETS reforms.

Table 6. TCI and transmission of volatility of carbon, dividing the sample into high and low emission firms

	Until 2018		2018-2020		2020-2024	
	HIGH	LOW	HIGH	LOW	HIGH	LOW
TCI	66.4%	72.1%	63.3%	66.6%	63.8%	61.1%
CO_2 TO	9.82%	11.96%	17.74%	14.82%	17.83%	21.71%

Note: TCI (Total Connectedness Index) and transmission of volatility of carbon (CO_2 TO) for the subsamples HIGH (high-emission firms) and LOW (low-emission firms) in the three sub-periods: from 2013 to 2018, from 2018 to 2020, and from 2020 to 2024.

3.6. CONCLUSIONS AND DISCUSSION

Climate change is a complex phenomenon and global collaboration between policy makers, public administrations, businesses and individuals is essential in order to identify strategies and implement policies and measures that are effective in mitigating its effects. Reducing emissions through the use of clean and renewable technologies, increasing carbon sinks, energy efficiency and reducing the carbon footprint of industries, transport and households are some of the mitigation strategies aimed at reducing GHG emissions that are essential to tackle global warming. In this way, regulated and voluntary carbon markets are key instruments to promote the reduction of GHG emissions, allowing companies to take on additional responsibilities by buying carbon credits from projects that reduce emissions (Bayon et al., 2012). In regulated carbon markets, carbon is priced, and companies can reduce their emissions by trading carbon credits.

Within the regulated markets, the first to be created was the EU-ETS (Directive 2003/87/EC of the European Parliament). When the EU-ETS was set up in 2005, it only covered CO_2 emissions from power stations and energy-intensive industrial sectors. Between 2005 and 2007, there was an over-allocation of allowances. Demand for allowances decreased as a result of the 2008 crisis, and the auctioning of allowances was introduced as the main allocation method in the third phase of the EU-ETS, which began in 2013. It was in this phase that more sectors and gases were included. Currently, the fourth phase (2020-2030) focuses on innovation in low-carbon technologies, modernization of the energy and industrial sectors and expansion into sectors such as maritime.

In this chapter, we apply the dynamic connectedness index of Diebold & Yilmaz (2012, 2014), combined with the decomposition of interdependence into frequency bands (Baruník & Křehlík, 2018), to measure the extent to which carbon shocks at one frequency (short- or long-term) influence the returns of high- and low-emitting firms. Specifically, we analyze volatility transmission between EU-ETS returns and the returns of high- and low-emitting European companies, differentiating between short- and long-term effects.

The findings reveal several key insights into the volatility transmission between carbon markets and corporate returns, highlighting the significant influence of regulatory and geopolitical events. Firstly, our results show that the connectedness between the EU-ETS and these companies is high and changes over the period of the third and fourth phase of the EU-ETS (from 2013 to 2024). Specifically, carbon volatility transmission increases over this period due to the implementation of EU-ETS reforms to accelerate decarbonization and meet EU climate targets. Secondly, this study also highlights that the majority of volatility transmission occurs in the short term (1–5 days), consistent across all sub-periods. This short-term dominance indicates that immediate market reactions to policy changes or economic events are a significant driver of volatility transmission. The temporal dynamics of connectedness confirms that major events (such as the adoption of the Paris Agreement and Brexit) significantly influence short-term market behavior.

Thirdly, carbon consistently appeared as a net receiver of volatility, receiving more from other market participants than it transmitted. This was particularly evident during periods of market uncertainty, such as Brexit and the COVID-19 pandemic. The findings align with prior research, such as Aslan & Posch (2022) and Suleman et al. (2023), which also noted carbon's role as a net receiver in the context of policy uncertainty. Fourthly, the results also indicate that while both high-emission and low-emission companies experience similar volatility transmission from carbon markets, the extent and dynamics differ slightly. High-emission companies, particularly in sectors like energy, mining, and finance, exhibit strong connections with carbon market volatility. In contrast, the transmission to low-emission companies, although slightly higher, is largely due to the inclusion of finance sector companies in this category, which are particularly sensitive to market-wide uncertainties.

As regards practical implications, it is important to note that the persistent increase in carbon volatility transmission throughout the study period reflects the growing impact of environmental regulations on corporate financial performance. As the EU-ETS continues to evolve, with more stringent measures to meet decarbonization goals, companies –regardless of their emission levels– must adapt their risk management strategies to mitigate the impacts of carbon market volatility. This study underscores the need for both policymakers and firms to consider the broader financial implications of carbon pricing mechanisms and environmental regulations.

Overall, this research contributes to understanding how carbon market volatility affects corporate returns in the EU context, highlighting the critical role of regulatory developments and market dynamics in shaping these interactions. Future research could further explore the sector-specific impacts of carbon market volatility and the effectiveness of corporate strategies in mitigating these risks. More specifically, while this study provides an overview of the impact of carbon market volatility on both high- and low-emission companies, future research could focus on sector-specific analyses. Examining how different industries (such as energy, finance, manufacturing, and technology) respond to carbon price changes could offer deeper insights. Moreover, future research could also examine the strategies that high-emission versus low-emission companies adopt in response to carbon market dynamics. This could include investments in renewable energy, changes in supply chain management, and shifts in product offerings. Examining case studies of companies that have managed carbon price volatility effectively can provide valuable insights and guidance for other organizations. Finally, future research could compare the effectiveness of the EU-ETS with other carbon pricing mechanisms or carbon markets, which would involve assessing the relative success of different approaches in reducing emissions, stabilizing markets, and fostering economic growth, as well as examining the challenges and opportunities of linking carbon markets across regions.

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CONCLUSIONS

There is no doubt that in recent years, governments and public institutions have had and still have to make efforts to implement public policies aimed at reducing greenhouse gas emissions of companies and others aimed at mitigating the negative effects of financial or health crises on liquidity and solvency, through different instruments, such as subsidies. Especially with the implementation of the European Union's Emissions Trading System reform and the health crisis resulting from the pandemic.

This PhD thesis seeks to improve knowledge about issues such as the implementation of public programs that intends to boot the attractiveness and appeal of investments in energy efficiency measures to mitigate climate change effects. Public investment subsidies are one of the most important tools to encourage companies to make such investments. Chapter 1 is aimed at identifying the profile of which SMEs display the greatest potential to invest in energy efficiency measures so that governments can direct their efforts towards such SMEs and thereby enhance the effective allocation and execution of these public policies. Based on a sample of 1,992 SMEs from the Region of Murcia (Spain) over the period 2013-2018, a random forest approach and techniques for unbalanced samples were used to identify SME profile.

Results show that the most useful predictors for predicting which SMEs in the industrial sector are potential energy beneficiaries are those related to liquidity and indebtedness. Moreover, based on the comparison of performance measures (specifically, with regard to informedness, precision, markedness, and F_1) between the random forest approach for unbalanced samples and traditional approaches (logit regressions), such as, results reflect a greater potential of using the random forest within this context, which makes it a suitable and accurate approach for determining which predictors affect the probability of SMEs requesting a public investment subsidy.

This PhD thesis also seeks to improve current understanding of government efforts consisted of adopting public policies to cushion the adverse effects of the COVID 19 pandemic on the liquidity and solvency of companies, since most of them saw their normal functioning and operations altered (Kahn & Wagner, 2021), with some even teetering on the brink of bankruptcy. In Spain, one of the key policies was the public guarantee policy, whose aim was to grant credit to companies so that they could continue to operate as normally as possible (ICO, 2020; *Real Decreto-Ley 25/2020, de 3 de julio, de medidas urgentes para apoyar la reactivación económica y el empleo*, 2020). This credit, targeted strictly at remedying short-term or temporary distress, was mainly directed towards SMEs and self-employed workers (ICO, 2020). In this context, by using a sample of Spanish SMEs, Chapter 2 focused on gauging the effect of the liquidity injection derived from this public policy on SMEs' optimal debt. Chapter 2 also aimed at examining to what extent the allocation of this public support, managed by banks, did or did not manage to remedy temporary distress.

Our results lead to two important conclusions. Firstly, although these public guarantees were useful in terms of preventing certain SMEs from going under (or, at least, reducing the severity of their economic decline), they triggered an increase in abnormal debt levels; in particular, in SMEs' long-term debt. Secondly, their allocation was not efficient, since they were not mainly directed towards SMEs who suffered a temporary downswing caused by COVID-19.

Lastly, this PhD thesis also attempts to contribute to the existing literature on the EU mitigation strategies aimed at reducing greenhouse gas emissions of companies, what are essential to tackle global warming. Specifically, Chapter 3 focuses on analysing the effects of EU ETS reforms to accelerate decarbonization on the carbon volatility transmission on low- and high-emission companies, differentiating between short- and long-term effects, during the third and fourth phases of the EU ETS (from 2013 to 2024). A sample of daily data of returns of 32 companies belonging to STOXX Europe 600 was used, 16 classified as high-emission companies, with an annual mean of direct C02 equivalent emissions over revenues of 1404.52 tonnes, and the remaining 16 with an annual mean of 4.03 tonnes. Based on this sample, the dynamic connectivity index of Diebold and Yilmaz (2012, 2014), combined with the decomposition of interdependence into frequency bands (Barunik and Krehlik, 2018), were used to measure the extent to which carbon shocks at one frequency (short- or long-term) influence the returns of high- and low-emitting companies.

The results show significant and time-varying connectivity between EU-ETS returns and the returns of both high- and low-emitting companies, driven by regulatory changes aimed at decarbonization. Notably, carbon volatility transmission increases over time (specifically, over the period of the third and fourth phase of the EU-ETS) and is similar across high- and low-emission companies, due in part to the sensitivity of the finance sector to EU-ETS shocks. We find that carbon acts as a volatility receiver, especially in energy-related sectors, with most spillovers occurring in the short term (1–5 days). These findings highlight the importance of carbon markets in shaping corporate financial performance and the need to understand volatility transmission under evolving environmental policies.