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Energy commodity spillovers and herding behavior: Evidence from EU ETS-listed firms

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Abstract

This paper analyzes the relationship between herding behavior and energy system's connectedness for a relevant sample of listed firms covered by the European Union Emissions Trading System (EU ETS). We analyze 345 EU ETS-listed firms, highlighting how connectedness is relevant in explaining the clustering of investment decisions, particularly during volatile market phases. Specifically, during distressed periods, higher energy system's connectedness fosters herding behavior, while a reduction in connectedness leads to greater investment dispersion. Moreover, a heterogeneity analysis across sectors and several robustness checks support these findings for energy firms, while revealing more mixed results for manufacturing companies. We further demonstrate that a buy-sell trading strategy, which incorporates market volatility and connectedness information to detect herding behaviors, provides superior risk-adjusted performance compared to alternative strategies, such as equally weighted buy-and-hold and minimum connectedness portfolios.

Keywords: herding behavior; spillovers; market volatility; market connectedness; EU ETS.

1 Introduction

Herding behavior spreads as investors' allocation decisions are driven not only by their own information set but are also influenced by the investment practices of other market participants, leading them to trade in a similar direction as a group (Banerjee, 1992, Trueman, 1994, Bikhchandani and Sharma, 2000). Such behavior can amplify market phenomena such as speculative bubbles and crashes, generating endogenous financial instability (Trueman, 1994, Zhao et al., 2011, Spelta et al., 2020).

Understanding herding is increasingly relevant for assessing the stability of financial markets exposed to environmental-related risks (Battiston et al., 2021, Flori et al., 2021). Environmental policies are informed by behavioral economics insights, with policymakers recognizing human behavior as a pivotal driver of many environmental challenges, such as global warming and climate change (Schubert 2017). In this context, firms are increasingly aware of the importance of signaling to investors their commitment to improving environmental outcomes, both to comply with regulatory monitoring requirements and to foster market performance (Konar and Cohen 2001, Dyck et al. 2019). Consequently, reducing the uncertainty about firms' environmental outcomes may lead investors to tilt their portfolios to assets with better environmental profiles (Starks et al. 2017, Avramov et al. 2022). However, during periods of market distress, investors may find it more challenging to accurately assess firms' commitment to environmental goals, as financial turbulence tends to amplify market comovements (Dajcman et al. 2012, Gjika and Horvath 2013). This can weaken firms' incentives to invest in costly cleaner technologies, implying that the effectiveness of green policies is closely linked to capital market dynamics and investor behavior (Krueger et al., 2020, Lee et al., 2023, Kruse et al., 2024).

We examine this issue in the context of carbon emissions trading schemes, a key policy instrument for promoting carbon abatement (Montgomery, 1972, Böhringer and Lange, 2005, Ellerman et al., 2016). In particular, we focus on the European Union Emissions Trading System (EU ETS), established in 2005, which is the world's largest carbon market. Each year, liable entities under the EU ETS are required to surrender an amount of permits corresponding to their verified emissions in the period. Hence, to comply with surrendering requirements, firms can either invest in cleaner technologies to reduce their carbon emissions or purchase additional allowances from the market.

In an efficient market, the carbon price should equalize marginal abatement costs across firms, ensuring cost-effective emission reductions (Montgomery, 1972, Salant, 2016). However, empirical evidence highlights several distortions in permit trading, including home-market and sectoral biases (Hintermann and Ludwig, 2023, Flori and Spelta, 2025), as well as transaction, information, and search costs that limit trade participation, particularly among smaller firms (Jaraitė et al., 2010, Abrell et al., 2022).

Capital market anomalies, such as herding, may represent an additional source of inefficiency influencing the functioning of the EU ETS. When prices do not efficiently incorporate all available information, this can increase investors' uncertainty and slow down the necessary learning process to identify the most profitable market opportunities. Therefore, individual investors start mimicking the actions of others, generating higher market volatility and deviations of prices from their fundamentals, which potentially leads to substantial and persistent impacts on financial markets (Park and Sabourian 2011, Bekiros et al. 2017). These distortions may inhibit firms from implementing long-term investments for carbon abatement, limiting the flow of information shared among participants and the positive impact of knowledge spillovers to clean innovation. Additionally, the uncertainty regarding the long-term sustainability of innovative cleaner technologies may induce investors to prefer firms with more traditional (but less clean) features, determining considerable delays in the implementation of green investments and the effectiveness of the environmental policies (Sengupta 2012, Flora and Tankov 2023).

Against this background, this paper examines the relationship between the functioning of the EU ETS, proxied by the connectedness of a representative set of energy commodities, and the market's response to shocks in terms of herding behavior observed in the stock returns of listed EU ETS-regulated firms. Our choice is based on the assumption that shocks generating sizeable connectedness among energy commodities affect the production activities and market performances of firms with an energy-related business (Oberndorfer, 2009, Nerlinger and Utz, 2022). These firms constitute a significant subset within the EU ETS in terms of emissions and participation in the trade of permits (Abrell et al., 2022, Zaklan, 2023, Flori, 2024).

More precisely, we test for the hypothesis that financial spillovers generated in a system of energy-related commodities significantly contribute to the variation in the EU ETS-listed firms' cross-sectional absolute deviation (CSAD) of returns. Hence, by estimating an augmented model to explain herding behavior based on the work of Chang et al. (2000), including the spillover variation as an additional regressor, we prove that the system's connectedness, as measured by the spillover index of Diebold and Yilmaz (2012, 2014), accounts for a critical role in explaining investment clustering.

We find that increases in spillover variations, reflecting higher market connectedness, intensify herding behavior, as indicated by lower CSAD values. Conversely, declining connectedness is associated with anti-herding patterns, characterized by higher CSAD. This relationship, particularly pronounced for energy-sector firms, remains robust across alternative estimation periods and parameter specifications.

We exploit this market inefficiency by exemplifying an application for the financial industry linking spillovers to the development of investment strategies associated with herding behaviors. We explore three simple buy-sell strategies for our sample of EU ETS firms, progressively incorporating additional factors such as market volatility and spillover variations. The first (H) strategy is purely based on market volatility to identify investment clustering, whereas the second (HS) and the third (HS+) ones also take into account the spillover variations. Based on risk-adjusted indicators, including the Sharpe ratio (SR) and the maximum drawdown (DD), we compare their performances with those of standard portfolio optimization methods, including a buy-and-hold equally weighted (B&H), a minimum connectedness (MC), and an equally weighted portfolio on the three indices (IN) used to compute the CSAD of returns in the main analysis. Overall, the inclusion of spillovers in the HS and HS+ strategies ensures better SRs (52.7% and 67.4%, respectively) and lower DDs (20.5% and 18.7%) than B&H (SR: 49.0%, DD: 40.9%), MC (SR: −6.0%, DD: 38.2%), and IN (SR: −4.8%, DD: 49.2%) portfolios. Importantly, these strategies are not deliberately optimized, as our goal is to demonstrate that the anomaly remains persistent and can be exploited even without resorting to sophisticated trading algorithms.

This paper is structured as follows. Section 2 provides the literature review on herding behavior and financial spillovers, describing how we establish the link between these two streams of research. Section 3 introduces the data and methodology we apply in our study. Specifically, we present the dataset integration employed in our study to link environmental data with market information. Section 4 shows the results of the empirical analysis, focusing on the relevance of the system's connectedness to improve herding-like detection. We then comment on the financial application based on the investment strategy grounded in the interaction between market volatility and the system's connectedness in Section 5. Lastly, the paper concludes by highlighting the contribution and limitations of our work in Section 6.

2 Literature review

Several theoretical motivations may explain herding behavior among investors, such as reducing information acquisition costs, reinforcing confidence through investment cascades, and minimizing reputational risk (Froot et al., 1992, Devenow and Welch, 1996, Graham, 1999).

Empirically, in developed markets, herding intensifies in periods of stress such as the global financial crisis, the 2010 Flash Crash, oil price collapses, and the COVID-19 pandemic (Mobarek et al., 2014, Demirer et al., 2019, Bouri et al., 2021). In emerging markets, it also reflects reactions to geopolitical uncertainty or commodity price swings, while greater market openness typically mitigates imitation (Yao et al., 2014, Cakan et al., 2019).

Recent studies highlight the role of informational dynamics in shaping herding intensity. For instance, Philippas et al. (2020) demonstrate that informative signals originating from exogenous factors, such as macroeconomic or technological developments, can generate spillovers that act as collective triggers, amplifying or dampening herding behavior in cryptocurrency markets. Similarly, Philippas et al. (2021) show that information loss indicators affect investors' attention and translate into greater cross-sectional dispersion across four sectors of the U.S. equity, including industrials and utilities.

From a methodological standpoint, herding detection ranges from cross-sectional dispersion models to network-based approaches (Chang et al., 2000, Diebold and Yilmaz, 2012, Diebold and Yılmaz, 2014) Recently, Tsionas et al. (2022) introduce a multivariate stochastic volatility framework that captures nonlinear comovements in returns and improves herding identification.

We extend previous literature by examining the determinants of herding behavior within the EU ETS. Our analysis reveals that herding intensity is not uniform across sectors: it is stronger among energy firms than in manufacturing activities. This sectoral heterogeneity suggests that market participants' behavioral responses are shaped by firms' exposure to energy and carbon-related dynamics. These results refine prior evidence showing that herding varies across industries, with higher levels in energy, basic materials, and consumer services, and weaker patterns in technology and industrial goods sectors (Zhou and Lai, 2009), and highlight the importance of incorporating environmental and policy dimensions into the study of financial behavior.

The other stream of research we contribute refers to the system's connectedness. In our paper, we measure the system's connectedness based on the approach of Diebold and Yilmaz, (2012, 2014). In such a framework, the system's connectedness is measured through financial spillovers, representing the shock transmission across assets in interconnected financial systems (see, e.g., Apostolakis and Papadopoulos 2015, Bratis et al. 2020, Chiappari et al. 2024, Drakos and Moratis 2024).

Due to the progressively higher integration of financial markets, spillovers can occur through various channels, including asset price movements, volatility changes, or liquidity shocks, potentially affecting market participants' investment behavior (Elsayed et al., 2020, Wen et al., 2021). Empirical evidence reports strong values of connectedness during periods of instability and uncertainty (Lyu et al., 2025). For instance, spillovers rise during the global financial crisis or the oil price drop of 2014 (Ferrer et al., 2018, Nasreen et al., 2020), at the outbreak of the COVID-19 pandemic (Jebabli et al., 2022, Li et al., 2022, Huang et al., 2023) and the Russia-Ukraine war (Adekoya et al., 2022, Wang et al., 2022). Given the empirically observed higher levels of spillovers during turbulent market phases, we expect its role in the detection of herding to be substantial when combined with higher market volatility. For example, asymmetric spillovers are identified in the upper and lower tails of the shock distribution, with more significant levels of connectedness displayed for more positive disturbances during the pandemic (Iqbal et al., 2022, Ghosh et al., 2023).

Spillover measures have also been applied to portfolio design, showing that overweighting green bonds (Broadstock et al., 2022) or renewable energy stocks (Bai et al., 2023) can create minimum-connectedness portfolios that outperform variance, or correlation-based strategies. Similarly, clean energy stocks reduce risk in mixed portfolios (Chen et al., 2022), and trading strategies incorporating spillover information can enhance returns (Iwanicz-Drozdowska et al., 2021).

Our paper contributes to expanding the literature on factor models by highlighting how spillovers, computed on a system of energy commodities, account for a critical role in explaining herding behavior. Investment strategies linked to herding behavior have received increasing attention from global investment managers and funds that have launched, for instance, specific exchange-traded funds (ETFs) based on market sentiment and stock return momentum.[1] Although both the level of market connectedness and the degree of shock transmission across financial assets may affect the investment decisions of market players, the extant literature has not yet investigated the relationship between herding behavior and financial spillovers within

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[1] Stock return momentum refers to the empirically observed tendency for rising asset prices or securities returns to continue increasing while falling prices tend to keep decreasing. This market anomaly has been leveraged by financial products such as ETFs. An example is the iShares Edge MSCI World Momentum Factor ETF, launched by BlackRock on October 3, 2014. This ETF tracks stocks with high price momentum from 23 developed countries worldwide. As of June 30, 2023, it had assets under management (AUM) of approximately \$1.53B (`https://www.blackrock.com/lu/individual/products/270051/ishares-msci-world-momentum-factor-ucits-etf`).

the EU ETS framework.[2]

Herding and connectedness provide actionable signals for asset allocation, revealing shifts in market sentiment and systemic risk (Klein, 2013, Galariotis et al., 2015). We extend the Chang et al. (2000) model by incorporating spillover variations and market volatility, linking systemic dynamics to investor behavior. Our analysis demonstrates that strategies exploiting these signals outperform traditional approaches, including equal-weight buy-and-hold and minimum connectedness portfolios (Broadstock et al., 2022), highlighting a novel way to leverage behavioral and systemic information for investment decisions.

3 Data and methods

This section outlines the data sources and empirical methods used to achieve our research objective. Figure 1 provides an overview of the key inputs for the analysis.

First, we present the set of listed companies under the EU ETS framework, as detailed in Section 3.1.1. Next, we gather data on the market indices (see Section 3.1.2) that are necessary for calculating the CSAD of returns, i.e. the dependent variable in the econometric model used to investigate herding behavior. We then construct a system of energy commodities to calculate the spillover index, as explained in Section 3.2. Finally, we develop an empirical model to examine the relationship between investment dispersion and system's connectedness in Section 3.3.

3.1 Stock and market returns

3.1.1 EU ETS-listed firms identification

In 2005, the European Commission (EC) launched the EU ETS to promote the reduction of GHG emissions in compliance with the Kyoto Protocols and international carbon neutrality targets by 2050.[3] The EU ETS initially consisted of three phases: Phase I (2005-2007), Phase II (2008-2012), and Phase III (2013-2020). Since 2021, the EU ETS has entered Phase IV (2021-

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[2] The link between herding behavior and market connectedness has been studied within other frameworks. For instance, Bouri et al. (2022) study the effect of investor sentiment on return and volatility spillovers of ten developed markets.

[3] Source: `https://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:2003:275:0032:0046:en:PDF`.

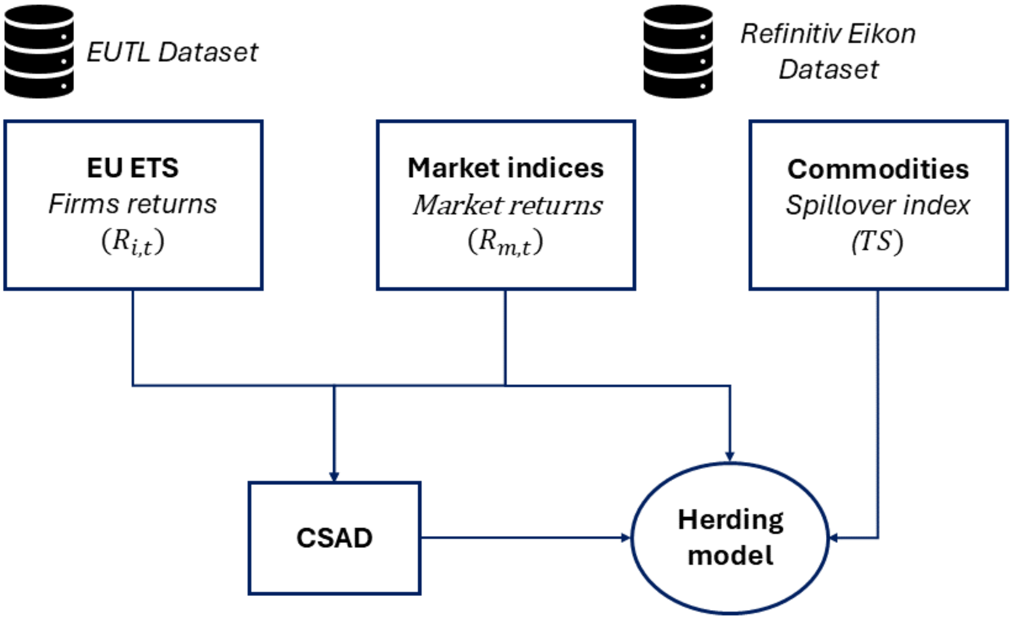

Figure 1: Logical flows underlying the data and methods Section.

2030). Further, by 2023, the EU ETS covered approximately 40% of the European Union's greenhouse gas emissions (European Commission, 2023). The EU ETS operates based on the principle of "cap and trade", meaning that installations associated with a liable entity must collectively comply with a specific limit on GHG emissions (Ellerman et al. 2016, Hintermann et al. 2016). The progressive reduction in the cap is designed to encourage environmental innovation and ensure a decrease in overall emissions. Relatedly, the European Union Allowances (EUAs) certify the emissions each liable entity can produce. Each allowance enables the holder to emit one metric tonne of CO_2 (or its equivalent). Firms that generate fewer emissions than their allocated allowances can retain the excess permits for future use or sell them to other participants facing a shortage in allowances. As of 2020, the EU ETS accounted for approximately 90% of global carbon market trading[4].

Information on EU ETS entities is retrieved from the European Union Transaction Log (EUTL), a central reporting and monitoring system for EU ETS data.[5] This repository contains information on the amount of verified emissions, allowances allocation, and surrendering, as well as permit transactions among accounts. All installations are associated with an operating holding account (OHA), a liable entity managing allowances operations to comply with

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[4] Source: `https://www.refinitiv.com/content/dam/marketing/en_us/documents/gated/reports/carbon-market-year-in-review-2020.pdf`.

[5] Source: `https://ec.europa.eu/clima/ets/`.

emissions verification and surrendering requirements.[6] Each OHA is linked to an Account Holder, representing the entity that owns the installation and manages the associated account. Multiple OHAs can refer to the same account holder. Our analysis aggregates data at the account holder level, focusing exclusively on publicly traded firms that owned at least one EU ETS installation between 2009 and 2022, following previous research on listed firms regulated by EU ETS (Chiappari et al., 2025a,b).

We link the EUTL data with different databases to obtain environmental, economic, and financial information on listed companies in the EU ETS perimeter (see, e.g., Abrell et al. 2022, Flori et al. 2024). We use the Bureau van Dijk (BvD) ID number to match EUTL and ORBIS[7] databases and identify the set of listed firms.[8] We also control for the company registration number and the name and address in the EUTL for the matching procedure with the ORBIS dataset. We find 8,623 entities owing at least one installation with associated emissions larger than zero in at least one year in our sample period.[9] Then, we restrict our analysis to firms publicly listed on European stock exchanges based on the availability of the *Ticker symbol*. At this stage, our sample encompasses 439 firms and reports information related to aggregate verified emissions, representing the amount of tonnes of emissions produced during the compliance year by the set of regulated entities (installations) controlled by the same firm. Finally, we obtain daily information on the market closing price of companies' stocks from LSEG Workspace.[10] We use the company *Legal Entity Identifier (LEI)* as a primary variable to match the previously matched sample and LSEG Workspace information.

At the end of this procedure, our sample covers 345 listed firms, mainly established in the manufacturing (64%) and energy (12%) sectors, while the other sectors cover around 24%. From a geographical perspective, our dataset encompasses 25 EU countries. The largest portion of firms is located in Germany (14%), followed by Poland (10%), Italy (8%), the UK[11] (8%), Romania (8%), France (6%), and Spain (6%), with the other countries accounting for about

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[6] We exclude from our analysis aircraft holder accounts since they entered the EU ETS framework in 2012-2013 and present peculiar characteristics.

[7] Source: `https://orbis.bvdinfo.com`.

[8] We rely on the work of Letoutt et al. (2021) disclosed by the Joint Research Centre (JRC) of the European Commission, which produced a dataset where they matched EU ETS account holders from the EUTL with companies in Bureau van Dijk - ORBIS.

[9] We exclude firms with verified emissions equal to zero from our study to avoid including firms that have ceased their operations but may still be registered within the EU ETS.

[10] Source: `https://www.lseg.com/en/data-analytics/products/workspace`.

[11] The UK Emissions Trading Scheme replaced the UK's participation in the EU ETS starting from 1 January 2021.

40%. Further details on the sector and country composition of our EU ETS sample are shown in Figure 2. Our sample is consistent with the listed companies under the EU ETS examined in De Beule et al. (2022) to investigate the impact of environmental regulation stringency across countries on the location of foreign direct investments. Additionally, it is comparable to the sample employed by Brouwers et al. (2016) scrutinizing EU ETS-listed companies to investigate the stock price variation caused by emission verification events.

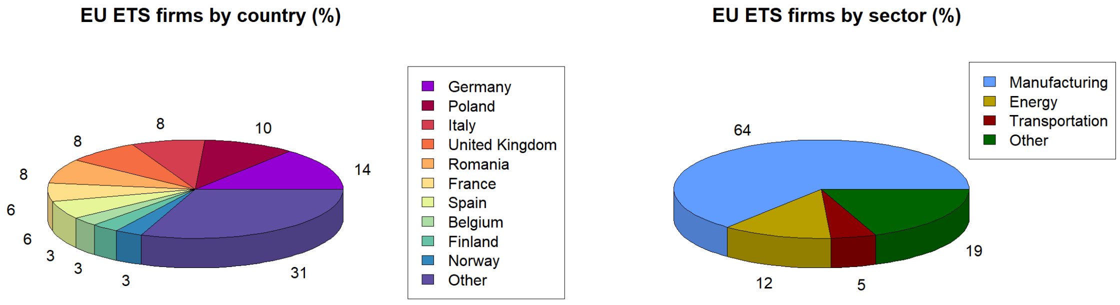

Figure 2: Country and sector composition of EU ETS firms.

From the daily closing prices of stocks of our EU ETS listed companies (P_t at time t), we compute the natural logarithmic returns as $r_t = \ln(P_t) - \ln(P_{t-1})$. Table 1 shows descriptive statistics of the three groups we analyze: the whole sample of listed EU ETS firms and the firms established in the manufacturing and energy sectors. Our data range from May 26, 2009,[12] to February 28, 2023.

We find that EU ETS firms have, on average, an almost null daily performance, regardless of the chosen sample. The whole sample experiences a higher standard deviation (3.0%) compared to the manufacturing (2.8%) and energy (2.2%) sectors. Interestingly, energy firms' returns are slightly left-skewed. This means that most observations are above the mean, with long left tails with negative returns that may result, for instance, from the substantial downturn of commodity prices in correspondence with the 2014-2015 global commodity markets crisis and the start of the COVID-19 pandemic. On the other hand, the whole sample and the manufacturing sector are characterized by substantial right-skewed returns. Furthermore, in all cases, the kurtosis

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[12] This is the first day from which the MSCI EMU Ex Financials Index time series is available on LSEG Workspace (see Section 3.1.2), while the other considered time series are available from previous dates compared to that of MSCI EMU Ex Financials Index. Additionally, it is worth noting that the first phase of the EU ETS (which ended in 2007) was a pilot phase.

exceeds three, meaning a leptokurtic distribution typical for financial assets.

The Jarque-Bera (JB) test rejects the null hypothesis of normal distribution at the 1% significance level for all samples. We perform the Augmented Dickey-Fuller (ADF) and the Phillips-Perron (PP) tests to detect the stationarity of the time series. The null hypothesis of unit root is rejected at the 1% significance level, providing strong evidence in favor of the stationarity of our system. Finally, we employ the Ljung-Box Q (LB) tests, which show that returns have significant serial autocorrelations. Indeed, the LB rejects the null hypothesis for all series at the 1% level for up to the 5^{th} and the 20^{th} order serial correlation.

	mean	median	std.dev	skewness	kurtosis	JB	ADF	PP	LB (5)	LB (20)
Whole	0.000	0.000	0.030	5.713	951.471	28,302,848,236.000***	−85.346***	−799,519.800***	1,453.804***	2,973.063***
Manufacturing	0.000	0.000	0.028	2.276	986.183	16,009,134,368.000***	−68.920***	−427,579.700***	3,029.824***	5,431.379***
Energy	0.000	0.000	0.022	−0.004	19.016	841,471.800***	−43.593***	−85,559.490***	551.605***	621.861***
Note:										*p<0.1; **p<0.05; ***p<0.01

Table 1: Descriptive statistics of firms' returns for each sample. JB column reports the statistics of the Jarque-Bera test for the null hypothesis of Gaussian distribution. ADF and PP denote the statistics of the Augmented Dickey-Fuller and Phillips-Perron unit root tests, respectively. LB (l) is the Ljung-Box statistics for up to the l^{th} order serial correlation.

3.1.2 Market indices

To compute the CSAD, we collect the daily closing prices of three indices, namely the MSCI EMU Ex Financials Index (contract .dMIEUMFN00PUS), MSCI Europe Industrials Index (contract .MIEU0IN00PEU), and MSCI Europe Energy Index (contract .MIEU0EN00PEU). They are representative of the whole sample, and the manufacturing and energy sectors in which EU ETS-listed firms typically operate, respectively. Table 2 shows that these market indices display very similar average returns as single stocks but significantly lower standard deviations (between 1.5% and 1.8%) than the corresponding EU ETS firms. Moreover, they are left-skewed, leptokurtic, non-normal, and stationary. Interestingly, the whole sample returns do not show a significant autocorrelation for up to the 5^{th} order serial correlation.

	mean	median	std.dev.	skewness	kurtosis	JB	ADF	PP	LB (5)	LB (20)
MSCI EMU Ex Financials	0.000	0.000	0.015	-0.618	12.318	$13,055.380^{***}$	-14.412***	$-3,304.724^{***}$	7.965	42.017**
MSCI Europe Industrials	0.000	0.001	0.016	-0.321	11.528	$14,309.750^{***}$	-15.133***	$-4,347.998^{***}$	21.577***	72.883***
MSCI Europe Energy	0.000	0.000	0.018	-0.305	15.717	$31,716.310^{***}$	-17.654***	$-4,473.053^{***}$	13.413**	63.261***
Note:										*p<0.1; **p<0.05; ***p<0.01

Table 2: Descriptive statistics of indices' returns. JB column reports the statistics of the Jarque-Bera test for the null hypothesis of Gaussian distribution. ADF and PP denote the statistics of the Augmented Dickey-Fuller and Phillips-Perron unit root tests, respectively. LB (l) is the Ljung-Box statistics for up to the l^{th} order serial correlation.

3.2 Market connectedness

3.2.1 Commodity series

The functioning of the EU ETS market might be strongly affected by energy price variations (Hintermann, 2010, Koch et al., 2014). For instance, the growth of fossil fuel prices may induce faster obsolescence of dirty technologies and foster green innovation. Similarly, lower renewable energy prices might stimulate a faster transition toward green technologies (Acemoglu et al., 2012, Aghion et al., 2016). Consequently, energy price variations may influence innovation and technology adoption, which relate to the demand for allowances and, therefore, the dynamics of the carbon price. Carbon market prices may thus affect EU ETS market participants' investment decisions that might be directed toward more brown or green technologies. As carbon prices promptly react to shocks from energy markets, we decide to compute volatility spillovers on a system of energy commodities strongly linked with EU ETS firms' business activities (see Section 3.2.2 for further details on spillover computation). Importantly, to be included in the EU ETS perimeter, firms must significantly contribute to GHG emissions (Lund 2007, Laing et al. 2013, Branger et al. 2016). Energy-intensive firms are thus typically covered by this regulation, with the power generators contributing for almost half of the GHG emissions (Zaklan, 2023).

Specifically, we collect the daily closing prices of six energy commodities (Brent Oil, Coal, Natural Gas, Ethanol, Gasoline, and Heating Oil), the European Union Allowances, and the Electricity from LSEG Workspace. Overall, our system of commodities provides a representative overview of the energy sector as they significantly contribute to satisfying both energy production and consumption requirements. For example, as of 2020, oil and petroleum products (e.g., gasoline and heating oil), natural gas, and coal accounted for around 70% of the gross available energy in the EU, while oil, gas, and coal and their derivatives covered about 60% of total consumption, playing a key role in the overall energy consumption regarding final usage;[13] in 2022 the EU produced almost 38.6% of electricity from fossil fuels, with gas constituting the most employed fossil fuel (19.6%), followed by coal (15.8%) and oil (1.6%).[14]

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[13] Source: `https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Energy_statistics_-_an_overview`.

[14] Source: `https://www.consilium.europa.eu/en/infographics/how-is-eu-electricity-produced-and-sold/`.

The sample comprises 3,544 daily observations, beginning on May 26, 2009, and ending on February 28, 2023. Specific futures contracts used in our study are listed in Table 3.[15]

Commodity	Contract	Description
Brent Oil	LCOc1	ICE - Brent Oil TRc1
Coal	ATWMc1	ICE - Coal Rotterdam TRc1
Phelix Electricity	EBMC.01	EEX - Phelix Baseload M TRC1
Ethanol	NEVCS01	NYMEX - Chicago Ethanol Platts Continuous LTDT
EUA	CFI2Zc1	ICE ENDEX - European Union Allowance
Gasoline	LHUCS01	ICE - NYH Gasoline (RBOB) Continuous LTD
Heating Oil	LHOCS01	ICE - Heating Oil Continuous LTD
Natural Gas	TRNLTTFMc1	ICE - Natural Gas TRc1

Table 3: Variable description as defined in LSEG Workspace.

Our spillover analysis is based on a system composed of the volatility time series of the selected commodities. To estimate the daily volatilities, plotted in Figure 3, we use a variety of GARCH models. Precisely, we follow the approach of Ferrer et al. (2021), who consider several alternative symmetric and asymmetric GARCH-type specifications (sGARCH, eGARCH, gjrGARCH, iGARCH, TGARCH, AVGARCH, NGARCH, NAGARCH, APARCH, and ALL-GARCH) under different error distributions (normal, skewed normal, Student-t, skewed Student-t, generalized error distribution, and skewed generalized error distribution) to estimate the conditional variance of the time series. The best fit is given by the couple of GARCH model and error distribution that minimizes the Bayesian information criterion (BIC).

Table 4 shows descriptive statistics of volatilities for the entire sample period. We find that commodities have an average volatility of around 2.9%, with a significant standard deviation (on average, around 2.3%). All volatilities appear to be right-skewed. This means that the majority of observations are below the mean, while long right tails with high volatilities may be a consequence of the substantial downturn of commodity prices in correspondence with the global commodity markets crisis of 2014-2015 and the start of the COVID-19 pandemic, as well as the significant increase in market prices after the beginning of the Russia-Ukraine war.

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[15] When available, our data refer to the futures price of commodities listed on a European exchange (e.g., Brent oil) instead of those quoted on an extra-EU financial market (e.g., West Texas Intermediate, i.e., WTI). Further, we consider the prices in euros to avoid bias related to currency appreciation or depreciation when computing returns.

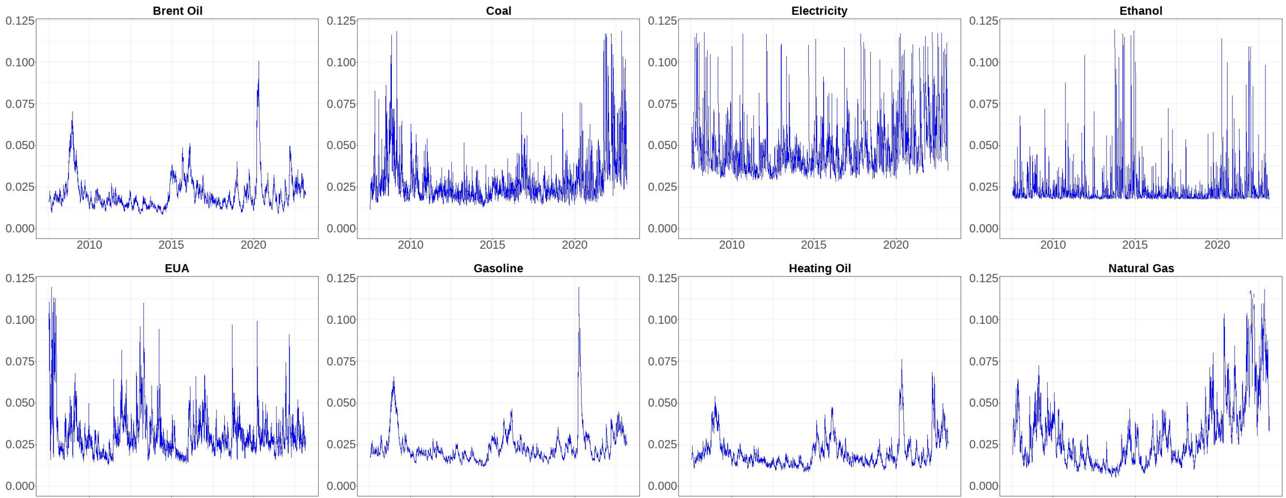

Figure 3: Volatilities of commodities. We report for each commodity the optimal GARCH model and error distribution selected using Bayesian information criterion (BIC): Brent oil (fGARCH, skewed Student-t), coal (fGARCH, skewed Student-t), electricity (eGARCH, Student-t), ethanol (iGARCH, Student-t), EUA (eGARCH, Student-t), gasoline (fGARCH, skewed Student-t), heating oil (fGARCH, skewed Student-t), and natural gas (fGARCH, skewed Student-t).

Additionally, commodities show a leptokurtic distribution.

The Jarque-Bera test rejects the null hypothesis of normal distribution at the 1% significance level for all series. The Augmented Dickey-Fuller and the Phillips-Perron provide strong evidence in favor of the stationarity of our system of commodities. Finally, the results of the Ljung-Box Q tests show that volatilities have significant serial autocorrelations.

	mean	median	std.dev.	skewness	kurtosis	JB	ADF	PP	LB (5)	LB (20)
Brent Oil	0.021	0.018	0.011	2.662	12.997	21,751.890***	-5.312^{***}	-50.399^{***}	19,270.100***	67,761.650***
Coal	0.030	0.024	0.019	5.354	52.108	428,402.300***	-7.799^{***}	-366.301^{***}	13,110.660***	24,610.170***
Electricity	0.052	0.044	0.036	10.922	200.388	6,688,230.000***	-12.089^{***}	$-1{,}132.428^{***}$	6,301.121***	8,397.455***
Ethanol	0.024	0.020	0.012	5.491	45.092	320,901.700***	-13.219^{***}	-977.110^{***}	6,197.311***	6,874.547***
EUA	0.034	0.028	0.061	26.747	852.496	122,863,934.000***	-11.231^{***}	-645.198^{***}	7,384.755***	11,045.940***
Gasoline	0.024	0.021	0.011	3.529	22.173	70,783.200***	-5.173^{***}	-48.468^{***}	19,406.660***	68,293.270***
Heating Oil	0.020	0.017	0.010	2.084	8.304	7,716.173***	-4.967^{***}	-60.089^{***}	19,189.750***	65,788.380***
Natural Gas	0.032	0.025	0.023	2.417	12.147	18,151.970***	-5.718^{***}	-86.801^{***}	19,075.280***	63,930.950***

Table 4: Descriptive statistics of commodity volatilities. JB column reports the statistics of the Jarque-Bera test for the null hypothesis of Gaussian distribution. ADF and PP denote the statistics of the Augmented Dickey-Fuller and Phillips-Perron unit root tests, respectively. LB (l) is the Ljung-Box statistics for up to the l^{th} order serial correlation.

3.2.2 Spillover index

As a first step, we measure the spillover index introduced by Diebold and Yilmaz (2012, 2014) (hereinafter DY). In this way, we measure how shocks on our system of commodities introduced in Section 3.2.1, namely Brent Oil, Coal, Electricity, Ethanol, EUAs, Gasoline, Heating Oil, and Natural Gas, impact the forecast error variances. This measure of connectedness hinges on the variance decomposition of a VAR model with P lags and K endogenous variables, approximating a covariance stationary process:

$$Y_t = \sum_{i=1}^{P} \Phi_i Y_{t-i} + \eta_t = \Phi(L) Y_t + \eta_t \tag{1}$$

where $Y_t = (Y_{1,t}, Y_{2,t}, ..., Y_{K,t})'$ constitutes a vector of volatilities observed in day t, $\Phi(L) = [I_K - \Phi_1 L - ... - \Phi_P L^P]$ is a $(K \times K)$ matrix of polynomials in the lag operator L, with I_K being the identity $K \times K$ matrix, and $\eta_t \sim (0, \Sigma)$ constitutes a vector of error terms whose covariance Σ may be non-diagonal.

Therefore, we regress the daily volatilities of each commodity on a set of regressors encompassing P lags of all commodities in the system (including the underlying variable itself). We can rewrite this VAR system based on a moving average representation with infinite order, VMA(∞), where we recursively define coefficient matrices Ψ_j, with $\Psi_0 = I$ and $\Psi_j = 0$ for $j < 0$. In formula:

$$Y_t = \sum_{j=0}^{\infty} \Psi_j \eta_{t-j} \tag{2}$$

$$\Psi_j = \Phi_1 \Psi_{j-1} + \Phi_2 \Psi_{j-2} + ... + \Phi_p \Psi_{j-p} \tag{3}$$

We rely on the Koop et al. (1996) and Pesaran and Shin (1998) (hereinafter KPPS) generalized vector autoregressive framework to compute variance decomposition. In this way, our estimates are not dependent on the order of the variables in our system of commodities. Based on such an approach, the KPPS H-step-ahead forecast error variance decomposition (FEVD) can be computed as:

$$\theta_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' \Psi_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' \Psi_h \Sigma \Psi_h' e_i)} \tag{4}$$

where Σ is the covariance matrix of the disturbance term η, σ_{jj} are diagonal terms of Σ, and e_j is a vector whose elements are all equal to zero, except for the term in position j that is equal to one. The term $\theta_{ij}(H)$ constitutes the extent to which the j^{th} commodity of our system contributes to the forecast error variance of the i^{th} commodity at the horizon H.

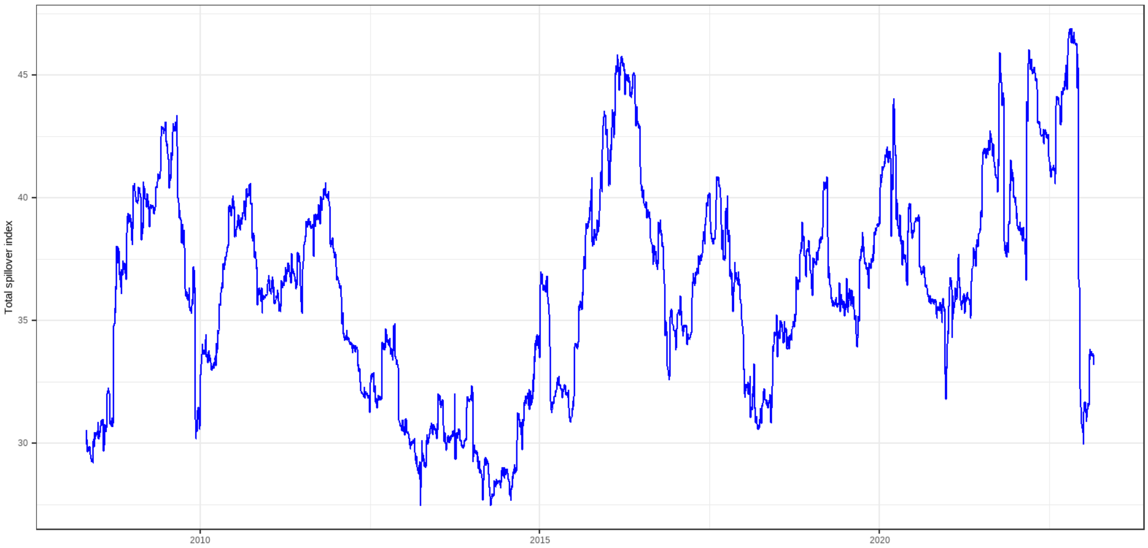

Figure 4: Total spillover index. We estimate the total spillover index using a VAR model with a 200-day rolling window size, a lag length of order one (SIC), and a 10-step-ahead generalized FEVD for the time domain following Diebold and Yilmaz (2012).

This approach does not guarantee that all rows sum to 1. Indeed, in general, the sum of own (diagonal terms of $\theta(H)$) and cross-variable (off-diagonal terms of $\theta(H)$) variance contributions is different from one ($\sum_{j=1}^{K} \theta_{ij}(H) \neq 1$). For this reason, we follow the DY approach by dividing each element of the variance decomposition matrix by its row sum:

$$\tilde{\theta}_{ij}(H) = \frac{\theta_{ij}(H)}{\sum_{j=1}^{K} \theta_{ij}(H)} \tag{5}$$

with $\sum_{j=1}^{K} \tilde{\theta}_{ij}(H) = 1$ and $\sum_{i,j=1}^{K} \tilde{\theta}_{ij}(H) = K$ by construction.

More generally, the total spillover index (Figure 4) provides a system-wide measure of connectedness, expressed as:

$$TS(H) = \frac{\sum_{j,k=1, j\neq k}^{K} \tilde{\theta}_{jk}(H)}{K} \cdot 100 \tag{6}$$

This index captures the (cross-) contribution of spillovers from shocks across all variables to the total forecast error variance. The spillover dynamics is quantified using a VAR model with a 200-day rolling window size, a lag length of order one obtained by minimizing the Schwarz information criterion (SIC), and a 10-step-ahead generalized FEVD for the time domain following Diebold and Yilmaz (2012) (see Figure 4).

3.3 Herding behavior model

We employ the estimation procedure proposed by Chang et al. (2000) and related to the CSAD of returns. According to Chang et al. (2000), during periods of significant price movements, a non-linear relation holds between stock return dispersion and market performance. To capture this effect, they compute the CSAD as follows:

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N}|R_{i,t} - R_{m,t}| \tag{7}$$

where N is the number of stocks in the considered market, $R_{i,t}$ is the log return of the i^{th} stock on day t, and $R_{m,t}$ is the market log return on the same day. In our analysis, $R_{i,t}$ and $R_{m,t}$ are the daily log-returns of the EU ETS stocks and of the three market indices discussed in Sections 3.1.1 and 3.1.2, respectively.

According to their model, the non-linear relationship between stock return dispersion and market performance can be estimated as:

$$CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R^2_{m,t} + \epsilon_t \tag{8}$$

where $R^2_{m,t}$ captures the non-linearity in the relation, and ϵ_t is the error term.

We apply Bohl et al. (2017)'s method to test for the presence of herding behavior. This involves comparing γ_2, estimated from Equation 8, with γ_2^0, indicating the value of γ_2 under the assumption of no herding.[16] Then, we use these values to compute the test statistic $T = \hat{\gamma}_2 - \hat{\gamma}_2^0$. As a general rule, the null hypothesis of no herding is rejected when $|T|$ is sufficiently large. To determine the critical value, we estimate the distribution of T through a bootstrap simulation.[17]

In our analysis, we aim to extend Chang et al. (2000)'s model by relating the relevance of herding behavior affecting EU ETS-listed firms with the variation of connectedness in energy-

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[16] For more information on the estimation of γ_2^0, see pages 2-4 of Bohl et al. (2017). Following the argument by Bohl et al. (2017), herding should not be identified by a negative and significant value of γ_2 relative to zero, as originally proposed by Chang et al. (2000), but rather by deviations of γ_2 from its true theoretical value under the null of no herding, denoted as γ_2^0. Intuitively, even in the absence of herding, stock returns are not perfectly aligned with the market due to idiosyncratic risk, which introduces a natural convexity in the relationship between return dispersion (CSAD) and market returns. This intrinsic convexity implies that γ_2^0 is positive, not zero. Consequently, testing whether γ_2 is smaller than zero leads to biased inference, pushing results toward detecting "anti-herding". Based on Bohl et al. (2017), the correct approach is to test whether the estimated $\hat{\gamma}_2$ significantly differs from its theoretical no-herding benchmark $\hat{\gamma}_2^0$.

[17] Details of the simulation can be found in Bohl et al. (2017), specifically on pages 6-8.

commodities system.[18] We do this by including the interaction term between the total spillover index variation, used as a proxy for changes in the connectedness of the system, and the squared market return, as an indicator of volatility in the market. Furthermore, the spillover variation and its square are added as additional control variables to account for asymmetric behaviors of such variations on herding. Thus, we propose to estimate the following model on daily data:

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R^2_{m,t} + \gamma_3 \Delta Spillover_t \times (R^2_{m,t}) + \gamma_4 \Delta Spillover_t + \gamma_5 \Delta Spillover^2_t + \epsilon_t \tag{9}$$

where $\Delta Spillover_t$ represents the logarithmic variation of the total spillover index (see Section 3.2.2) on day t.

While a significant Bohl et al. (2017)'s test on γ_2 indicates the existence of domestic herding in market m, a significantly negative γ_3 suggests that positive spillover variations enhance herding, especially in turbulent phases, by reducing the CSAD of returns. In this way, we aim to contribute to the herding literature by introducing the interaction between market volatility and spillover variation as an additional key factor influencing investor behavior. As noted in Section 2, connectedness tends to rise during periods of market distress. Given that large squared market returns signal high volatility, and positive spillover variations reflect increasing market connectedness, we expect a significantly negative γ_3.

Indeed, increased system instability and higher shock transmission are likely to intensify investment clustering. This perspective is particularly informative for investors, financial entities, and policymakers, as herding behavior has traditionally been explained by market volatility alone. Understanding the interaction between volatility and spillovers could help predict herding, enabling market participants to make more informed decisions by detecting this behavior earlier. Section 5 provides a financial application that demonstrates how spillover information can offer better signals of herding-like phenomena.

Lastly, we include $\Delta Spillover_t$ and $\Delta Spillover^2_t$ as control variables to balance the distributional effects of the spillover variations. While we expect spillover variations to significantly

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[18] Other authors have proposed extensions of Chang et al. (2000)'s model. For instance, Gavrilakis and Floros (2023) have recently proposed to examine the asymmetric behavior of returns dispersion concerning the interaction with ESG performances as follows:

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R^2_{m,t} + \gamma_3 ESG \times (R^2_{m,t}) + \epsilon_t$$

where ESG is the average performance of the yearly ESG scores.

influence herding in periods of high market instability, they may have a weaker effect during tranquil periods. Hence, we expect that, on average, changes in connectedness alone are not sufficient to explain investment dispersion if not combined with the information on market volatility conditions. Nonetheless, large spillover variations can be interpreted as signals of abrupt changes in the system that may generate endogenous instability and more heterogeneity in the allocations. We aim to capture the latter effect by means of the squared spillover variations. In the analysis presented in Section 4.1, we estimate both a parsimonious model that excludes these controls and nested specifications that progressively include them. We anticipate that the main relationships involving γ_3 will remain qualitatively similar across models.

All models are tested on our sample of ETS-listed firms and separately for the manufacturing and energy sectors. Our choice is motivated by the structural relevance of these two sectors within the EU ETS framework. Energy producers and manufacturing firms represent the most emission-intensive industries and are therefore the primary participants in the EU carbon market (see Figure 2). Concentrating on these sectors allows us to explore sector-specific dynamics where the interaction between energy system connectedness and firms' market behavior is most meaningful. At the same time, by keeping the full sample in our baseline estimations, we ensure that our findings remain representative of the overall EU ETS-regulated market while allowing for a deeper examination of the sectors that play a pivotal role in its functioning.

Additionally, in all our models, we employ the heteroscedasticity and autocorrelation consistent estimators by Newey and West (1987) to address the autocorrelation issue in the estimates of regression coefficients.

4 Empirical results

Section 4.1 is dedicated to examining herding behavior within the EU ETS focusing on how spillovers among energy commodities described in Section 3.2.1 contribute to this market anomaly, particularly in the energy sector. Further checks in Sections 4.2.1, 4.2.2, 4.2.3, 4.2.4 and 4.2.5 point to confirm this result.

4.1 Herding evidence

Table 5 displays the results of the daily analysis of the CSAD described in Equation 8 in the whole sample (column 1), in the manufacturing (column 2) and energy (column 3) sectors, as well as of Bohl et al. (2017)'s test statistics. Coefficient γ_1 is positive and statistically significant at the 1% level in all cases. Additionally, γ_2 is positive but not statistically significant in the whole sample and in the manufacturing and energy sectors. These results relate to a relevant portion of previous literature showing a significant linear but not significant quadratic relation between the CSAD and the return of the market (see, e.g., Christie and Huang 1995, Chan et al. 2000, Babalos et al. 2015, Bohl et al. 2017, Zhou et al. 2022). However, to more accurately verify whether the estimated γ_2 is associated with herding behavior, we perform the Bohl et al. (2017)'s test, which compares the estimated γ_2 coefficient with the estimated γ_2^0 parameter representing the correct benchmark estimate to assess the presence of herding behavior when the condition of identically zero idiosyncratic components does not hold. In particular, if $\hat{\gamma}_2$ is significantly lower than $\hat{\gamma}_2^0$, this provides evidence of herding behavior.

The results of the Bohl et al. (2017)'s test can be summarized as follows. In the whole sample, we get $\hat{\gamma}_2^0 = 4.721$. The test statistic is $|T| = 3.3924$, with a critical value of $|\tilde{T}| = 2.5561$ at the 1% level. In the manufacturing sector, we obtain $\hat{\gamma}_2^0 = 2.366$ and a test statistic of $|T| = 1.9831$, with a critical value of $|\tilde{T}| = 1.8026$ at the 1% level. In the energy sector, we get $\hat{\gamma}_2^0 = 1.855$ and a test statistic of $|T| = 2.1740$, with a critical value of $|\tilde{T}| = 1.9474$ at the 1% level. Overall, we provide therefore evidence of herding behavior in all three cases.

Table 6 refers to the results of the daily analysis of the CSAD described in Section 3.3 in the whole sample (columns 1-3), in the manufacturing (columns 4-6) and energy (columns 7-9) sectors. Compared to Table 5, we add a regressor to the simple model one at a time. Specifically, we insert the interaction between the spillover variation and the squared market returns, then the spillover variation, and, finally, the squared spillover variation to get our extended model described by Equation 9.

	Dependent variable: CSAD		
	Whole Sample	Manufacturing	Energy
Intercept	0.013***	0.012***	0.011***
	(0.0002)	(0.0002)	(0.0002)
(γ_1) Abs. market ret.	0.313***	0.310***	0.423***
	(0.037)	(0.033)	(0.024)
(γ_2) Sqr. market ret.	1.040	0.596	0.693
	(0.839)	(0.773)	(0.495)
Bohl et al. (2017)'s test statistics for γ_2	3.392***	1.983***	2.174***
Observations	3,543	3,532	3,480
R^2	0.578	0.510	0.581
Adjusted R^2	0.577	0.509	0.581

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 5: Estimation of γ_2 and Bohl et al. (2017)'s test statistics in the whole sample (column 1), in the manufacturing (column 2) and energy (column 3) sectors.

We then explore to what extent aspects related to the EU ETS functioning, proxied by the connectedness in our energy commodity system, may have contributed to the presence of such herding behavior in the sample period. Interestingly, columns 1, 2, and 3 of Table 6 illustrate that spillover variations enhance herding when interacting with market volatility, since we find a significantly negative γ_3. These results are also confirmed when analyzing the manufacturing sector (column 6 of Table 6) and, in particular, the energy sector (columns 7, 8, and 9 of Table 6), although the former displays a slightly lower significance in favor of herding (5% vs. 1%). Such findings complement, for instance, previous evidence obtained by Gavrilakis and Floros (2023), who extend the traditional herding model through an interaction term between the squared market returns and ESG scores. They find a negative coefficient for the interaction term, suggesting that herding in the market is stimulated by higher ESG scores. Our significantly negative γ_3 consistently demonstrates that the interaction between high market volatility and rising spillovers provides better signals of investment clustering.

By contrast, γ_4 does not seem to statistically differ significantly from zero, except for the most extended model for manufacturing firms (column 6) at the 10% level. This proves that higher connectedness induces investment clustering when combined with large values of market volatility, while spillover variations alone are not sufficient to explain the CSAD of returns. On the other hand, we find that γ_5 is significantly positive at the 5% level for the whole sample (column 3) and manufacturing firms (column 6) but not for energy firms (column 9), although

	Dependent variable:								
	CSAD								
	Whole Sample			Manufacturing			Energy		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	0.013^{***}	0.013^{***}	0.013^{***}	0.012^{***}	0.012^{***}	0.012^{***}	0.011^{***}	0.011^{***}	0.011^{***}
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
(γ_1) Abs. market ret.	0.322^{***}	0.321^{***}	0.322^{***}	0.309^{***}	0.308^{***}	0.307^{***}	0.414^{***}	0.413^{***}	0.412^{***}
	(0.032)	(0.031)	(0.030)	(0.031)	(0.030)	(0.029)	(0.021)	(0.021)	(0.020)
(γ_2) Sqr. market ret.	0.843	0.838	0.807	0.635	0.645	0.664	0.942^{***}	0.957^{***}	0.970^{***}
	(0.654)	(0.647)	(0.627)	(0.696)	(0.688)	(0.653)	(0.385)	(0.344)	(0.335)
(γ_3) Spillovers var. * Sqr. market ret.	-19.563^{**}	-20.616^{**}	-23.546^{***}	−13.289	−15.125	-20.991^{**}	-18.308^{***}	-19.507^{***}	-20.843^{***}
	(8.477)	(8.533)	(8.616)	(10.958)	(11.143)	(10.432)	(4.877)	(4.227)	(4.046)
(γ_4) Spillovers var.		0.006	0.015		0.005	0.014^{*}		0.014	0.018
		(0.007)	(0.008)		(0.007)	(0.007)		(0.013)	(0.014)
(γ_5) Sqr. spillovers var.			0.364^{**}			0.344^{**}			0.284
			(0.168)			(0.149)			(0.211)
Observations	3,543	3,543	3,543	3,532	3,532	3,532	3,480	3,480	3,480
R^2	0.579	0.582	0.584	0.511	0.512	0.514	0.582	0.584	0.585
Adjusted R^2	0.578	0.581	0.583	0.510	0.511	0.514	0.582	0.584	0.584
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$								

Table 6: We show the output of the herding model described in Section 3.3 for the whole sample of firms (columns 1-3), the manufacturing (columns 4-6) and the energy sectors (columns 7-9). The dependent variable is the daily CSAD of returns. The first, fifth, and ninth columns represent the model described in Equation 8. Other columns progressively add the interaction between the spillovers variations and the squared market returns, the spillovers variation, and the squared spillovers variations as additional regressors to get our extended model described by Equation 9.

the coefficient is still positive. We argue that higher squared spillover variations refer to major changes in the connectedness of the system that may lead to less stability in the spillover transmission and, thus, to higher CSAD.

4.2 Robustness analyses

4.2.1 Lagged model

Table 7 presents the results of the lagged herding model and follows the same structure as Table 6, previously discussed in Section 4.1. In this specification, the spillover-related regressors are lagged to test for the absence of reverse causality between the CSAD and spillover variations.[19] The appropriate lag length is selected by minimizing the Akaike Information Criterion (AIC) in a VAR(p) framework, where the CSAD is regressed on spillover variations. This procedure consistently selects a lag of 4 days across all three cases.

The results from the lagged model largely align with those in Table 6 in terms of the statistical significance of the regressors. Notably, some differences mainly emerge in the manufacturing sample: in column 5, γ_4 becomes statistically significant, and in column 6, both γ_4 and γ_5 exhibit increased statistical significance. The magnitude of the coefficients remains broadly consistent across the two tables. However, γ_3 appears more negative in the lagged model, suggesting a stronger anticipatory role of spillovers in explaining CSAD dynamics.

4.2.2 Dummy variable model

Following prior studies (e.g., Christie and Huang 1995, Chang et al. 2020, Gouta and Ben-Mabrouk 2024), we identify extreme market movements by selecting the 5% of sample observations located in the tails of the distribution of spillover variations. This procedure allows us to capture periods of heightened connectedness and detect potential herding behavior under extreme conditions. To account for the impact of these extreme spillover movements, we extend Equation 9 as follows:

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[19] To further verify the direction of the relationship, we conducted a Granger causality test between the daily spillover variation and the CSAD. Results show that spillover variation Granger-causes CSAD at the 1% significance level ($p = 0.002$), while the reverse causality is not supported ($p = 0.356$). This indicates that increases in market connectedness precede and predict stronger herding behavior, rather than the opposite.

	Dependent variable:								
	CSAD								
	Whole Sample			Manufacturing			Energy		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	0.013***	0.013***	0.013***	0.012***	0.012***	0.012***	0.011***	0.011***	0.011***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
(γ_1) Abs. market ret.	0.266***	0.260***	0.259***	0.275***	0.270***	0.268***	0.412***	0.410***	0.409***
	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
(γ_2) Sqr. market ret.	0.915	0.928	0.992	0.639	0.657	0.707	0.946***	0.977***	0.990***
	(0.816)	(0.863)	(0.834)	(0.616)	(0.621)	(0.621)	(0.318)	(0.304)	(0.298)
(γ_3) Spillovers var. * Sqr. market ret.	−31.852***	−32.110***	−32.571***	−14.794	−16.869	−22.156**	−31.960***	−35.676***	−37.631***
	(7.293)	(7.626)	(7.620)	(15.218)	(16.125)	(11.018)	(4.294)	(4.403)	(4.434)
(γ_4) Spillovers var.		0.022	0.029		0.016***	0.022**		0.030	0.040
		(0.019)	(0.030)		(0.006)	(0.011)		(0.029)	(0.038)
(γ_5) Sqr. spillovers var.			0.236**			0.264***			0.407
			(0.122)			(0.084)			(0.320)
Observations	3,539	3,539	3,539	3,528	3,528	3,528	3,476	3,476	3,476
R^2	0.593	0.596	0.597	0.535	0.540	0.542	0.601	0.604	0.615
Adjusted R^2	0.593	0.595	0.596	0.534	0.539	0.540	0.601	0.603	0.612
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$								

Table 7: We show the output of the lagged herding model described in Section 3.3 for the whole sample of firms (columns 1-3), the manufacturing (columns 4-6) and the energy sectors (columns 7-9). The dependent variable is the daily CSAD of returns. The first, fifth, and ninth columns represent the model described in Equation 8. Other columns progressively add the interaction between the spillovers variations and the squared market returns, the spillovers variation, and the squared spillovers variations as additional regressors to get the lagged version of our extended model described by Equation 9.

$$
\begin{aligned}
CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \gamma_3 \Delta Spillover_t \times R_{m,t}^2 + \gamma_4 \Delta Spillover_t \\
+ \gamma_5 \Delta Spillover_t^2 + \gamma_6 D_t^{Up,spill} \times R_{m,t}^2 + \gamma_7 D_t^{Down,spill} \times R_{m,t}^2 + \epsilon_t
\end{aligned}
\tag{10}
$$

Here, the dummy variables $D_t^{Up,spill}$ and $D_t^{Down,spill}$ capture instances of extreme positive and negative spillover variations, respectively. Specifically, $D_t^{Up,spill} = 1$ if the spillover variation falls within the top 5% of its empirical distribution, and $D_t^{Down,spill} = 1$ if it falls within the bottom 5%. Consistent with our earlier findings, we expect the coefficient γ_6 to be negative, as herding behavior is typically more pronounced during periods of extreme spillover shocks.

Table 8 shows indeed that the coefficient γ_6 is negative and statistically significant across all model specifications and subsamples, indicating that when spillover variations reach exceptionally high and positive levels, reflecting abrupt increases in cross-market connectedness, returns tend to cluster more tightly around the market average. This reduction in CSAD is a clear sign of amplified herding behavior under extreme systemic connectedness.

In contrast, the coefficient γ_7 is positive, particularly within the energy sector, implying that during periods of sharply declining spillover activity, market participants behave more heterogeneously, consistent with anti-herding or divergent trading behavior.

4.2.3 Distressed events

Table 9 investigates whether herding behavior intensified in the year following major systemic disruptions, namely the 2014–2015 Global Commodity Price crisis (columns 1, 4, 7), the COVID-19 pandemic (columns 2, 5, 8), and the Russia–Ukraine war (columns 3, 6, 9). Across all panels, the interaction term between spillover variations and squared market returns (γ_3) is negative and highly significant, confirming that during crisis periods, stronger market interconnectedness systematically reduces the cross-sectional dispersion of returns. This pattern is consistent with intensified herding behavior, as investors tend to align their strategies more closely when uncertainty and systemic stress are elevated.

Among the three crises, the Russia–Ukraine war exhibits the largest (in absolute value) and most significant coefficients, particularly for the energy sector (column 9). This result highlights how shocks directly affecting energy markets and geopolitical risk channels foster synchronous

	Dependent variable:					
	CSAD					
	Whole Sample		Manufacturing		Energy	
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.013***	0.013***	0.012***	0.012***	0.011***	0.011***
	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
(γ_1) Abs. market ret.	0.318***	0.352***	0.309***	0.344***	0.405***	0.420***
	(0.010)	(0.040)	(0.028)	(0.038)	(0.025)	(0.035)
(γ_2) Sqr. market ret.	0.804	1.248	0.441	1.558	1.089*	1.221**
	(0.766)	(1.492)	(0.658)	(1.352)	(0.594)	(0.521)
(γ_3) Spillovers var. * Sqr. market ret.		−19.847**		−17.721**		−22.145***
		(8.554)		(7.304)		(7.832)
(γ_4) Spillovers var.		0.009		0.009		0.024
		(0.008)		(0.009)		(0.028)
(γ_5) Sqr. spillovers var.		0.291**		0.275**		0.320
		(0.139)		(0.138)		(0.207)
(γ_6) $D^{Up,spill}$ * Sqr. market ret.	−2.027**	−1.900**	−0.756**	−0.725**	−1.197***	−1.135***
	(0.840)	(0.776)	(0.327)	(0.301)	(0.424)	(0.388)
(γ_7) $D^{Down,spill}$ * Sqr. market ret.	0.405	0.315	0.526	0.432	0.953**	1.088*
	(0.907)	(0.900)	(0.581)	(0.586)	(0.640)	(0.637)
Observations	3,543	3,543	3,532	3,532	3,480	3,480
R^2	0.586	0.599	0.516	0.558	0.586	0.627
Adjusted R^2	0.583	0.596	0.515	0.557	0.585	0.625
Note:	*p<0.1; **p<0.05; ***p<0.01					

Table 8: We show the output of the dummy variable model described for the whole sample of firms (columns 1-3), the manufacturing (columns 4-6) and the energy sectors (columns 7-9). The dependent variable is the daily CSAD of returns. The first, fifth, and ninth columns represent the model described in Equation 8. Other columns progressively add the interaction between the spillovers variations and the squared market returns, the spillovers variation, and the squared spillovers variations as additional regressors to get our extended dummy variable model described by Equation 10.

trading patterns and amplify behavioral contagion. The COVID-19 pandemic also reveals substantial herding effects, though slightly less pronounced, reflecting the widespread yet uneven transmission of uncertainty across industries. In contrast, during the 2014–2015 commodity price collapse, the herding response appears weaker and more sector-specific, suggesting that market participants partially differentiated their reactions based on exposure to commodity fundamentals. In more general terms, each of these three high-uncertainty cases corresponds to γ_3 coefficients considerably higher than those estimated in Table 6.

Overall, these findings provide evidence that herding behavior is not only state-dependent but also crisis-specific. Periods of heightened systemic stress, especially those involving energy and geopolitical shocks, intensify collective market behavior, reinforcing the role of connectedness spillovers as a behavioral amplifier in times of crisis. This dynamic underscores the importance of monitoring systemic linkages and behavioral synchronization when assessing financial stability under extreme events.

4.2.4 The impact of market volatility and connectedness on herding behavior

We analyze the impact of market volatility and connectedness on herding behavior by estimating the value assumed by the CSAD in correspondence with several combinations of the squared market return and spillover variations. In particular, we divide the distribution of market volatility and spillover variations into 100 quantiles and plot the corresponding CSAD levels for each possible couple of values of the two variables.[20]

We do a comprehensive set of robustness checks to evaluate our findings. Specifically, the left plots of Figure 5 (panels A, D, G) assess the presence of herding for the CSAD levels computed by using the γ coefficients reported in columns 3, 6, and 9 of Table 6 for the whole sample, and the manufacturing and energy sectors, respectively. Further, the middle (panels B, E, H) and right plots (panels C, F, I) in Figure 5 illustrate the results obtained by utilizing the γ coefficients related to the minimum and maximum values they assume when employing a bootstrap procedure that considers a random sample based on 80% of all available observations

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[20] In this case, we estimate the CSAD as follows: $CSAD_t = \gamma_2 R^2_{m,t} + \gamma_3 \Delta Spillover_t \times (R^2_{m,t}) + \gamma_4 \Delta Spillover_t + \gamma_5 \Delta Spillover^2_t$. Compared to Equation 9, we neglect the contributions of α and $\gamma_1 |R_{m,t}|$ since we want to illustrate how the CSAD varies as a function of the squared market return and spillover variations, our variables of interest. This choice does not affect our final results since it just has a translation effect on the value of CSAD plotted in Figure 5, given that we are subtracting the same common value from all the computed CSAD levels.

	Dependent variable:								
	CSAD								
	Whole Sample			Manufacturing			Energy		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	0.015***	0.024***	0.016***	0.013***	0.020***	0.015***	0.013***	0.017***	0.015***
	(0.001)	(0.003)	(0.001)	(0.0005)	(0.003)	(0.001)	(0.001)	(0.002)	(0.001)
(γ_1) Abs. market ret.	0.407***	0.233***	0.277***	0.282***	0.411***	0.304***	0.336***	0.424***	0.366***
	(0.087)	(0.054)	(0.056)	(0.061)	(0.141)	(0.065)	(0.064)	(0.154)	(0.105)
(γ_2) Sqr. market ret.	0.695	0.760	0.735	0.672	0.996	0.917	0.863	0.820	1.107*
	(0.557)	(0.562)	(0.673)	(0.594)	(0.875)	(0.868)	(0.786)	(0.768)	(0.647)
(γ_3) Spillovers var. * Sqr. market ret.	−32.271***	−36.260***	−46.983***	−30.727***	−35.024***	−42.927***	−38.677***	−40.531***	−50.066***
	(10.942)	(9.417)	(12.642)	(10.639)	(10.121)	(8.206)	(9.182)	(9.070)	(12.563)
(γ_4) Spillovers var.	0.037**	0.035	−0.071	0.098***	−0.034	−0.162*	−0.032	0.016	0.143
	(0.016)	(0.077)	(0.052)	(0.033)	(0.148)	(0.083)	(0.035)	(0.113)	(0.150)
(γ_5) Sqr. spillovers var.	0.395	2.580**	3.420***	1.948***	0.860	1.695*	1.176	3.377	1.543
	(0.588)	(1.159)	(0.721)	(0.824)	(1.253)	(0.916)	(0.994)	(2.228)	(2.168)
Observations	252	252	252	252	252	252	252	252	252
R^2	0.509	0.445	0.639	0.484	0.422	0.618	0.527	0.483	0.650
Adjusted R^2	0.507	0.442	0.637	0.482	0.420	0.616	0.525	0.481	0.648
Note:	*p<0.1; **p<0.05; ***p<0.01								

Table 9: We show the output of the herding model described in Section 3.3 for the whole sample of firms (columns 1-3), the manufacturing (columns 4-6) and the energy sectors (columns 7-9), applied to distressed events. The dependent variable is the daily CSAD of returns. The first, fifth, and ninth columns represent the model described in Equation 8. Other columns progressively add the interaction between the spillovers variations and the squared market returns, the spillovers variation, and the squared spillovers variations as additional regressors to get the lagged version of our extended model described by Equation 9.

with 10,000 replications.[21]

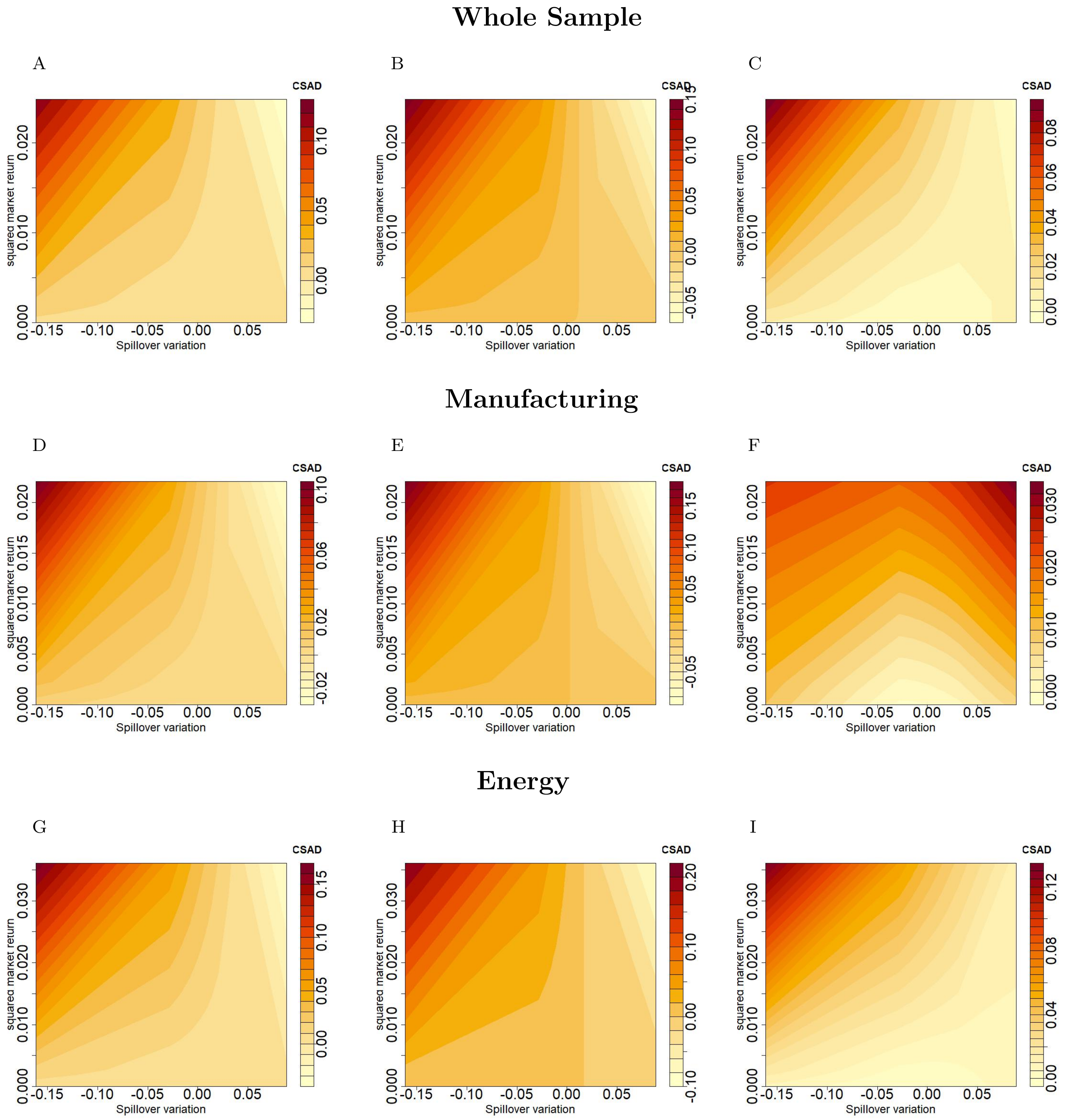

Figure 5: Contour plot illustrating the CSAD as a function of the spillover variation (x-axis) and the squared market return (y-axis). In this case, we compute the CSAD as $CSAD_t = \gamma_2 R^2_{m,t} + \gamma_3 \Delta Spillover_t \times (R^2_{m,t}) + \gamma_4 \Delta Spillover_t + \gamma_5 \Delta Spillover_t^2$ and show its level in correspondence with several combinations of the squared market return and spillover variations. We do so for the whole sample of firms (upper row) and then focus on firms established in the manufacturing (medium row) and energy (lower row) sectors. In all cases, the left column refers to the case where in Equation 9 we consider all estimated coefficients in the baseline scenario shown in columns 3, 6, and 9 of Table 6. The middle (right) column refers to the case where we use the minimum (maximum) coefficients estimated using a bootstrap procedure with a random sample that corresponds to 80% of all available observations with 10,000 replications.

Through this procedure, we aim to verify whether the negative interaction effect between

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[21] The bootstrap procedure is applied to compute γ coefficients by using the model specification reported in columns 3, 6, and 9 of Table 6 for the whole sample, and the manufacturing and energy sectors, respectively. Notably, it preserves the temporal order of sampled data.

market volatility and connectedness on CSAD also holds in extreme data configurations. The whole sample analyzed in Panel A of Figure 5 highlights how variations in the level of connectedness influence the relationship between the CSAD and squared market return. We prove that if market volatility is low (around zero), then the role of connectedness on the CSAD is marginal since the dispersion of returns ranges between $-1.44 \cdot 10^{-4}$ and $7.16 \cdot 10^{-3}$. Similarly, regardless the level of market volatility, limited changes of connectedness around zero have very modest effects on CSAD values, varying between $-2.50 \cdot 10^{-8}$ and $2.00 \cdot 10^{-2}$.

On the other hand, if the market volatility is high (around 2.5%), market connectedness appears to be relevant for the CSAD, corroborating the importance of including spillovers to explain herding. Indeed, during distressed phases, negative spillover variations (meaning a reduction of connectedness) are associated with anti-herding mechanisms since the CSAD tends to increase from $2.00 \cdot 10^{-2}$ to $1.20 \cdot 10^{-1}$. Conversely, we point to herding behavior in correspondence with significant levels of market volatility and positive spillover variations (suggesting an increase in connectedness) as the CSAD reaches the minimum values ($-2.68 \cdot 10^{-2}$).

The main results also hold when restricting the analysis to the manufacturing sector (see panels D and E in Figure 5). However, in this case, we cannot find evidence of herding behavior when using γ coefficients corresponding to the maximum values in the bootstrap replications (see panel F in Figure 5). Conversely, very similar results as those observed for the whole sample occur for the energy sector (see panels G, H, and I in Figure 5). Even in this case, different scenarios demonstrate that higher market volatility provides evidence of investment clustering for positive spillover variations. These findings suggest that the relevance of the spillover variations to explain herding-like phenomena, as measured in terms of CSAD, is more robust in the energy than in the manufacturing sector. This is likely due to the computation of the spillovers on a system of energy-related commodities, whose price variations mainly impact the market prices of firms with a more focused energy-related business.

4.2.5 Results stability

This Section assesses whether the results obtained in Section 4.1 are confirmed, even considering the uncertainty associated with the parameter estimates. We do this through a 10,000 replications bootstrap procedure, which computes the model described in Equation 9 by using a random sample with 80%, 85%, 90%, and 95% of observations.[22] In so doing, we are also re-estimating the herding model in different time windows.

For the whole sample, the upper panel of Figure 6 highlights that higher uncertainty with parameter estimates occurs when the bootstrap replications consider a smaller subsample. Yet, all coefficients display a limited estimate dispersion as they always maintain the same sign. The only exception is for the spillover variation coefficient when using only 80% of observations since the extreme distribution's lower tail assumes slightly negative values (see panel D in the whole sample subplot of Figure 6). Nonetheless, we still confirm the main findings of Section 4.1 (i.e., higher connectedness tends to reduce the CSAD in correspondence with higher market volatility) as the interaction term displays an entirely negative distribution.

Then, we replicate the same analysis for the manufacturing and energy sectors separately. Manufacturing firms exhibit a slightly higher heterogeneity. Indeed, the spillover variation and the interaction term with market volatility change their sign at the extremes of the lower and upper distribution, respectively (see panels D and F of the manufacturing subplot of Figure 6 for the manufacturing sector). This result can be related to the fact that these firms display some exceptions to the main findings of Section 4.2.4 when we consider extreme combinations of γ coefficients related to the maximum values of the bootstrap procedure.

On the other hand, we identify more homogeneous results for energy firms (see panels A-F in the energy subplots of Figure 6). Indeed, even when accounting for only 80% of observations to estimate the herding model, no replication produces coefficients with a different sign from that obtained in column 9 of Table 6. This finding is coherent with the fact that the relationship between market connectedness and herding behavior is more robust and stable for firms in this sector.

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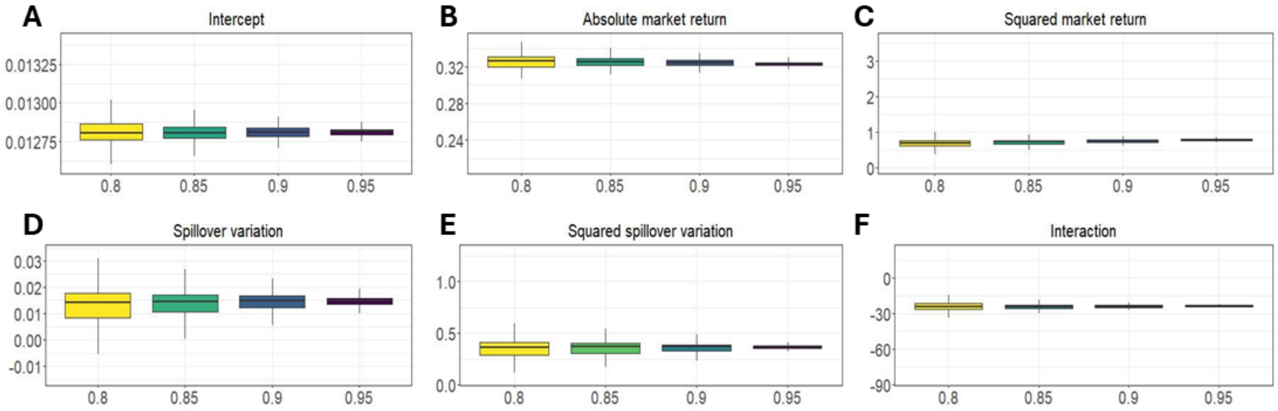
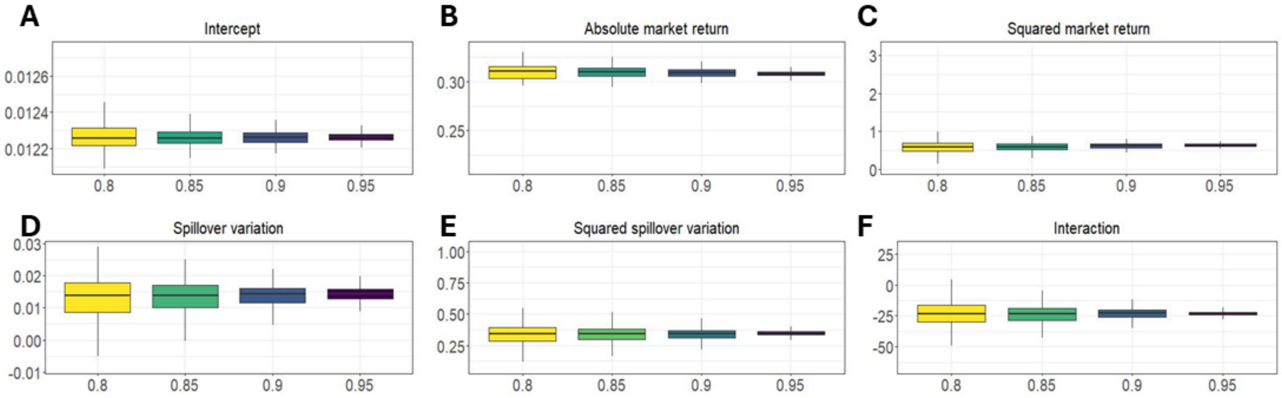
[22] Consistently with the previous Section, we preserve the temporal order of the sampled observations.

Whole Sample



Manufacturing



Energy

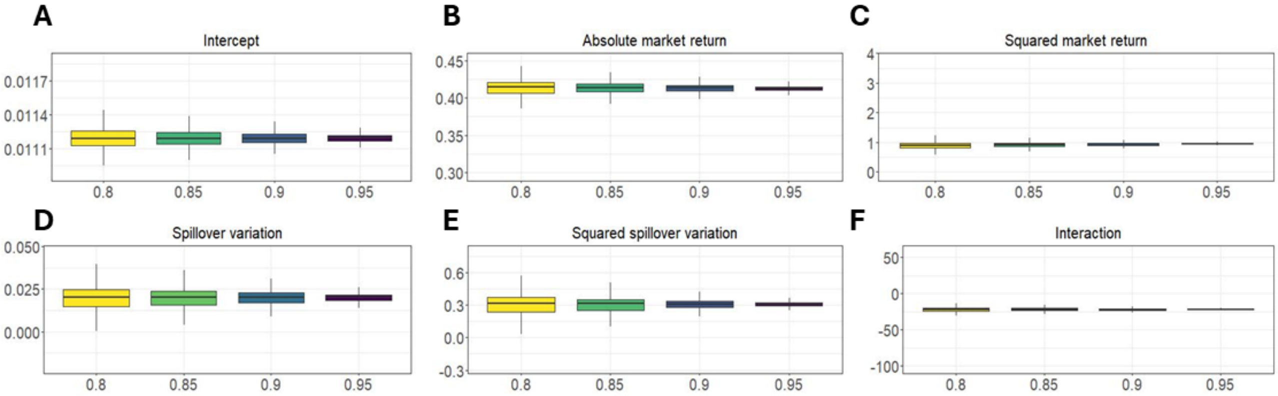


Figure 6: Box plots showing the distribution of all coefficients included in Equation 9 estimated through a 10,000 replications bootstrap. We use a random sample with 80%, 85%, 90%, and 95% of overall observations both for the whole sample of firms (upper panel) and for manufacturing (medium panel) and energy (lower panel) firms. Boxplots are colored based on the width of the inter-quantile range (IQR, difference between 75th and 25th percentiles). Darker colors refer to narrower IQR.

5 Portfolio application

The efficient market hypothesis states that prices quickly react when new information becomes available, and future returns cannot be predicted by past information. However, investors' cognitive biases and reactions to new information or shocks may question the theory of market efficiency (Lehmann, 1990, Jegadeesh and Titman, 1995). Indeed, market participants may adapt their investment strategies following the performance of their investments and the interactions with other investors, thereby generating non-trivial aggregate patterns within the financial systems (Hommes, 2006, Sornette, 2009, Scheffer et al., 2012, Flori et al., 2019) potentially leading to market instability (Durlauf, 2005, Scheffer et al., 2009).

Section 4 shows that combining the information on market volatility and spillover variations allows us to better identify herding-like behaviors. In this Section, we propose and test an application based on investment strategies built on the interaction between market volatility and spillover variations and we compare them with alternative portfolio strategies. Our results indicate that spillover information is helpful for the identification of herding signals.

Specifically, to show how connectedness can help build investment strategies, we implement three buy-sell equally weighted strategies on our sample of EU ETS-listed firms. The first strategy (H) is purely based on the market volatility of EU ETS firms to detect herding behavior, whereas the second (HS) and the third (HS+) further refine the previous strategy by including spillover variations. These strategies are not intentionally optimized, as our goal is to demonstrate that the anomaly remains persistent and can be exploited even without relying on sophisticated trading algorithms.

We compare the performances of our strategies with a standard buy-and-hold equally weighted (B&H) portfolio and a minimum connectedness (MC) portfolio built on the same sample. Further, we add to the comparison an equally weighted portfolio constructed on the three indices (IN) used to compute the CSAD in Sections 4.1 and 4.2 and described in Section 3.1.1.

5.1 Main strategy

Concerning our strategies, we propose basic indicators and simple decision rules for each trading day to guide buy and sell decisions and identify signals of potential herding-like behaviors. We opt to rely on a very parsimonious list of market variables: the daily spillover variation, the average 5-day EU ETS firms' returns, and the 20-day rolling standard deviation of EU ETS firms' returns. We believe this simple toolbox of parameters can provide a reasonable trade-off between data availability and the need to map common trading practices based on market signals. We evaluate the robustness of these choices via a sensitivity analysis, as shown below in Section 5.2. However, we anticipate that even though these parameters are not deliberately chosen based on optimization procedures, the results are still encouraging.

Specifically, we first compare the 20-day rolling standard deviation of EU ETS firms' returns with the 80^{th} quantile of the distribution of the previous 80-day volatilities, which sets a threshold above which we identify a distressed market phase and, thus, a possible investment entry point. Hence, we basically assume that signals of herding behaviors, if present, are better related to periods of high market instability, as discussed in Section 2.

We then introduce investment rules to guide the investor's decision whether to buy, sell, or remain neutral (not invested). The first strategy (H) works as follows. It starts with a neutral position; the next trading day, if the rolling EU ETS firms' volatility belongs to the right tail of the volatility distribution (i.e., it is a signal of a phase of market instability above the 80^{th} quantile), the strategy opens a position, due to the presence of potential herding behaviors. Specifically, it opens a long, equally weighted position on the stocks of the EU ETS-listed firms if the average 5-day EU ETS firms' return is positive. To follow the potential bullish trend due to positive momentum, the logic behind this long position is that timely detection of herding behaviors may allow the investor to benefit from a progressively increasing demand for these assets, leading to their market appreciation. Conversely, in case of a negative average 5-day EU ETS firms' return, the strategy opens a short, equally weighted position to avoid a potential bearish trend due to negative momentum. Even in this case, the timely identification of a phase of investment clustering combined with negative average EU ETS firms' returns may allow the investor to gain from a short decision due to a probable stronger divestment and price reduction of the underlying stocks. Otherwise, when the rolling EU ETS firms' volatility does not fall in the distribution's right tail, the strategy advises remaining neutral, and the algorithm is iterated the following day. Finally, during a buy (sell) phase, coherently with the entry rule, the algorithm exits the long (short) position if the EU ETS firms' volatility falls below the 80^{th}

distribution quantile of the previous 80-day EU ETS firms' volatilities, as herding behavior is assumed to be lessened.

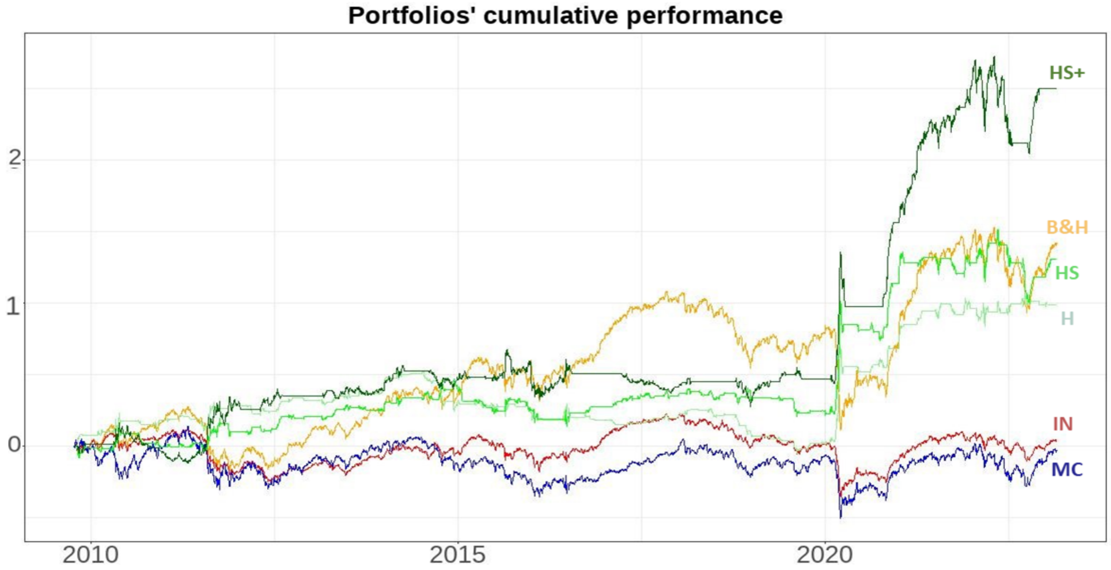


Figure 7: Cumulative gross performance of the analyzed strategies from May 2009 to February 2023.

HS and HS+ strategies open a position when both the H's entry conditions are satisfied and the spillovers variation is non-negative (i.e., market connectedness is not decreasing). This latter condition implies the presence of potential herding behavior amplified by rising spillovers as shown in Sections 4.1. Moreover, their exit conditions are also on spillover variations and should, thus, be able to better identify phases of market instability and their time evolution. Specifically, if the entry conditions hold, the cumulative return of spillover variations (CUM RET) is computed from the day the position is taken. More precisely, during a buy (sell) phase, HS and HS+ exit the long (short) position if, besides satisfying the condition on EU ETS firms' volatility required by H, CUM RET is below the threshold of 1, indicating herding behavior has lessened, and information spillovers in the system propagate more weakly. In addition, to accommodate a more focused risk perspective in the trading, HS+ has a second exit condition verified if, at least after 80 trading days from the position opening, the EU ETS firms' volatility falls below the 80^{th} quantile threshold and, differently from HS, CUM RET has had at least a 10% drawdown with respect to the maximum value of CUM RET observed during the opened position. The pseudo-code 1 summarizes our trading strategy HS+. Figure 7 shows the cumulative gross returns achieved by following either our proposed investment or alternative strategies.

		2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	Total
B&H	Return	1.535	15.558	−25.175	23.075	16.633	8.129	8.866	18.259	14.618	−20.703	12.233	−5.634	42.043	−8.240	9.843	146.720
	σ	16.762	16.812	20.313	14.173	9.677	12.100	14.895	18.376	7.216	10.878	10.351	29.029	13.569	17.669	8.663	15.951
	SR	40.909	83.685	−142.209	144.775	158.362	62.599	55.489	91.265	183.975	−205.893	108.486	−19.513	249.723	−47.539	650.159	48.996
	DD	7.343	15.654	35.606	16.115	9.492	11.356	15.216	18.180	3.805	25.967	11.486	40.940	7.368	24.169	1.035	40.940
MC	Return	0.777	6.702	−23.522	3.587	8.930	2.995	−0.889	11.388	13.861	−16.563	0.971	−11.067	18.372	−7.915	6.509	−9.441
	σ	12.563	12.823	15.646	10.759	8.392	12.114	13.265	14.130	6.224	9.059	8.389	23.057	10.040	13.178	6.467	12.722
	SR	27.738	49.219	−170.714	32.369	101.531	23.609	−6.553	76.322	202.941	−192.984	11.206	−49.685	162.201	−61.113	585.054	−5.963
	DD	5.607	13.061	29.200	16.610	12.249	11.550	17.273	14.106	3.528	19.371	13.051	38.163	6.489	18.922	0.823	38.163
IN	Return	−1.556	1.632	−20.769	11.006	16.185	−14.686	−13.288	7.105	20.620	−17.401	15.075	−11.964	17.646	−7.847	9.476	−2.988
	σ	27.641	25.342	32.366	22.207	14.523	13.080	18.706	25.394	9.880	15.383	13.596	40.357	17.460	26.892	15.489	22.777
	SR	−25.523	6.214	−71.645	46.464	102.885	−117.692	−74.159	27.031	184.618	−119.989	100.485	−30.839	89.868	−29.680	350.706	−4.770
	DD	9.915	25.220	40.854	22.252	11.610	22.568	22.003	16.547	3.646	26.279	14.330	49.195	9.886	31.513	2.741	49.195
H	Return	7.356	9.843	8.797	3.021	6.984	−8.069	−3.394	−5.712	0.899	−9.883	−4.566	63.956	16.743	1.029	−0.018	101.970
	σ	9.662	12.400	12.723	5.370	5.430	8.413	10.004	12.137	3.769	7.095	6.331	23.323	9.171	11.874	4.208	10.913
	SR	330.588	73.670	66.006	54.773	123.847	−96.927	−33.586	−48.464	23.109	−141.605	−71.835	207.060	162.979	8.421	−2.566	46.010
	DD	0.772	8.543	9.210	5.521	3.000	18.397	8.936	8.860	3.805	14.936	11.796	11.192	3.999	8.190	1.160	18.397
HS	Return	−1.190	0.845	10.392	9.505	3.480	12.783	−10.903	1.806	6.144	−1.030	−6.821	71.334	6.661	−4.369	5.683	135.532
	σ	13.186	12.996	16.230	6.520	5.468	8.981	10.303	11.375	5.241	7.981	5.798	23.654	9.811	12.304	5.741	11.596
	SR	−40.868	6.297	60.674	137.631	62.311	129.830	−109.021	15.739	110.697	−12.527	−118.557	222.337	63.463	−35.465	577.749	52.686
	DD	8.422	12.612	10.880	3.993	3.538	5.073	13.405	9.712	3.805	7.654	10.606	13.890	7.838	20.468	1.029	20.468
HS+	Return	1.443	−5.624	33.646	5.602	2.798	6.682	7.145	−5.002	−6.412	−6.908	12.036	74.091	37.716	−0.734	0.000	250.369
	σ	12.118	14.288	20.313	8.812	8.294	10.271	13.587	17.495	5.659	7.544	7.334	23.785	11.272	15.739	0.000	13.595
	SR	53.210	−39.418	142.209	61.131	33.143	61.037	49.422	−29.333	−113.928	−91.623	150.768	227.666	274.133	−4.570	NA	67.445
	DD	5.129	18.415	12.945	4.995	4.676	10.693	10.588	17.234	9.327	13.871	5.319	16.593	6.301	18.745	0.000	18.745

Table 10: Profit & Loss Analysis. We report the annualized and total gross returns, the standard deviation of returns (σ), Sharpe ratio (SR), and maximum drawdown (DD) for B&H, MC, IN, H, HS, and HS+ portfolios from May 2009 to February 2023. The results are expressed in percentages.

We evaluate the risk-return profile of the strategies by employing the standard deviation of the returns (σ), the Sharpe ratio (SR), and the maximum drawdown (DD). Table 10 reveals some interesting findings. First, the highest annual return for HS+ corresponds to about 74.1% (2020), comparable to H (64.0% in 2020) and HS (71.3% in 2020), while it is much lower for B&H (42.0% in 2021), MC (18.4% in 2021), and IN (20.6% in 2017). Notice how the HS+ strategy guarantees higher total returns (250.4%) than B&H (146.7%), HS (135.5%), H (102.0%), IN (-3.0%), and MC (−9.4%). Additionally, H, HS, and HS+ strategies generated better returns during the 2011 European debt crisis, the first year of the COVID-19 pandemic (2020), and the initial phase of the Russia-Ukraine war (2022), when B&H, MC, and IN portfolios had instead lower or even negative performances.

Secondly, even the volatility of returns experiences significant fluctuations, reaching around 23-24% in 2020 for all strategies, except for B&H and IN, which exceed 29% and 40%, respectively. Considering the whole period, H shows the lowest volatility (10.9%), followed by HS (11.6%), whereas HS+ and MC are a bit riskier (their σ is 13.6% and 12.7%, respectively), and the volatilities of B&H and IN are sensibly higher (16.0% and 22.8%). Consistently, exploiting increasing market connectedness leads to better risk-adjusted performances. For instance, over the entire period, higher SRs characterize HS (52.7%) and HS+ (67.4%) compared to H (46.0%), and B&H (49.0%). The SRs of MC and IN are even negative (−6.0% and −4.8%, respectively).

Algorithm 1: Portfolio Strategy with Herding Behavior and Spillover Analysis (HS+)

```
input: Stock price data ‘stockPriceMatrix‘ = $\begin{bmatrix} p_{1,1} & ... & p_{1,N} \\ ... & ... & ... \\ p_{T,1} & ... & p_{T,N} \end{bmatrix}$
Commodity price data ‘commodityPriceMatrix‘ = $\begin{bmatrix} q_{1,1} & ... & q_{1,K} \\ ... & ... & ... \\ q_{T,1} & ... & q_{T,K} \end{bmatrix}$
output: Portfolio strategy returns ‘strategyRet‘ = $\begin{bmatrix} R_1 & ... & R_T \end{bmatrix}'$
Step 1: Initialization
Set ‘T‘, ‘N‘, ‘K‘ as dimensions of ‘stockPriceMatrix‘ and ‘commodityPriceMatrix‘
Set rolling window volatility ‘w‘ ← 20, volatility distribution length ‘dVol‘ ← 80, return period ‘n‘ ← 5
Set ‘strategy‘ ← “neutral”
Initialize ‘portfolioRet‘, ‘spillRet‘, ‘strategyRet‘ as empty arrays
Step 2: Compute Portfolio and Spillover Returns
Calculate daily stock returns in ‘stockRetMatrix‘ = $\begin{bmatrix} r_{1,1} & ... & r_{1,N} \\ ... & ... & ... \\ r_{T-1,1} & ... & r_{T-1,N} \end{bmatrix}$ where $r_{t,i} = log(p_{t+1,i}) - log(p_{t,i})$
Compute equally-weighted portfolio returns, ‘portfolioRet‘, from ‘stockRetMatrix‘, as = $\frac{\sum_{t=1}^{T-1}\sum_{i=1}^{N} r_{t,i}}{N}$
Estimate daily commodity volatilities using a GARCH model on ‘commodityPriceMatrix‘ as explained in Section 3.2.1
Calculate ‘spillRet‘= $\begin{bmatrix} SR_1 & ... & SR_T \end{bmatrix}'$, where $SR_t = log(TS_{t+1}) - log(TS_t)$, and $TS_t$ is the spillover index (Eq. 6)
Step 3: Define and Execute Portfolio Strategy
1. for each trading day ‘t‘ from (‘dVol + w‘) to ‘T‘ do
    Compute the ‘w‘-days rolling volatility distribution ‘volatilityDistr‘ = $\begin{bmatrix} \sigma_1 & ... & \sigma_{dVol} \end{bmatrix}'$ over ‘dVol‘ days
    Compute the $80^{th}$ quantile ‘q‘ of ‘volatilityDistr‘
    Calculate the average ‘n‘-days stock returns ‘avgRet‘= $\frac{\sum_{t=1}^{n}\sum_{i=1}^{N} r_{t,i}}{N}$
    2. Determine Position:
    if ‘strategy‘ is “neutral” then
        Initialize the spillover growth rate ‘CAGR‘ ← 1, its maximum ‘maxCAGR‘ ← 1, days ← 1
        if $\sigma_{dVol}$ > ‘q‘ and ‘avgRet‘ > 0 and ‘spillRet[t]‘ ≥ 0 then
            Set ‘strategy‘ ← ”long”
        end
        else if $\sigma_{dVol}$ > ‘q‘ and ‘avgRet‘ < 0 and ‘spillRet[t]‘ ≥ 0 then
            Set ‘strategy‘ ← ”short”
        else
            Stay ”neutral”
        end
    end
    else if ‘strategy‘ is “long” then
        if (‘CAGR‘ < 1 and $\sigma_{dVol}$ < ‘q‘) or (‘CAGR‘ < 0.9 * maxCAGR and $\sigma_{dVol}$ < ‘q‘ and days ≥ ‘dVol‘) then
            Set ‘strategy‘ ← ”neutral”
        end
        else
            Stay ”long”
        end
    end
    else if ‘strategy‘ is “short” then
        if (‘CAGR‘ < 1 and $\sigma_{dVol}$ < ‘q‘) or (‘CAGR‘ < 0.9 * maxCAGR and $\sigma_{dVol}$ < ‘q‘ and days ≥ ‘dVol‘) then
            Set ‘strategy‘ ← ”neutral”
        end
        else
            Stay ”short”
        end
    end
    3. Compute strategy return
    if strategy is long then
        Store ‘strategyRet[t]‘ based on the ‘portfolioRet‘ of the corresponding trading day
    end
    else if ‘strategy‘ is “short” then
        Store ‘strategyRet[t]‘ based on the opposite of the ‘portfolioRet‘ of the corresponding trading day
    else
        Store ‘strategyRet[t]‘ ← 0
    end
    4. Update trading parameters
    Update ‘days‘ ← ‘days‘ + 1
    Update ‘CAGR‘ ← ‘CAGR‘ + ‘spillRet[t]‘
    Update ‘maxCAGR‘ as the maximum value of the cumulative return of the spillovers over the time window ‘days‘
end
return: ‘strategyRet‘
```

Finally, for standard portfolios, DD, quantifying the maximum loss accrued in each year compared to the peak value recorded in that period, appears to follow the dynamics of the financial cycle, with a sharp rise (in absolute value) in the crisis years and lower values during the tranquil phases. Overall, the maximum drawdown is 20.5% for HS in 2022 and 18.7% for HS+ in 2022, while for B&H it is 40.9% (2020), for MC 38.2% (2020), for IN 49.2% (2020), and for H 18.4% (2014). Further, based on DD, over the entire sample period, H and IN portfolios are the least and most risky in such a framework, respectively.

5.2 Sensitivity analysis

We perform a sensitivity analysis to check the robustness of our proposed strategy and evaluate how the results are affected by the specific hyper-parameters of our trading algorithm. We select HS+ as our preferred strategy based on portfolio performances. We vary the main hyper-parameters of the portfolio strategy on a grid of values centered around the values used to compute the performances in Table 10 and report in Figure 8 the updated results.

5.2.1 Volatility window

We consider varying lengths of the rolling window employed to compute the volatility distribution exploited to identify periods of market distress. Specifically, we center our grid of values at 80 days and we let the window vary from 75 to 85 days, with a step of 1. This allows us to preserve a sufficient sample size for calculating the empirical distributions while accounting for a variation of one trading week with respect to the benchmark case discussed in Table 10.

5.2.2 Volatility quantile

Similarly, we consider different values of the quantile of the volatilities' distribution used to initialize the strategy. We center the sensitivity analysis at 0.80 and we consider quantiles from 0.70 to 0.90, with a step of 0.02. This allows us to increase the potential days of herding-like phenomena when reducing the quantile, or being more restrictive in the identification of these cases when increasing it. As a result, when reducing (increasing) the quantile, we allow for more (fewer) trading operations.

5.2.3 Spillover thresholding

Then, we employ distinct levels of the CUM RET hyper-parameter, which we let vary between 0.85 and 1, the latter being the threshold used in the main analysis, with a step of 0.05. A lower CUM RET reduces the role of the spillover index in the exit rule of the strategy when the system's connectedness decreases.

5.2.4 Market return and standard deviation window

Finally, we vary the number of days over which the average returns of EU ETS firms are computed to identify phases of positive or negative market performance, allowing this window to take values of 1, 5, and 10 days. At the same time, we adjust the rolling window for the standard deviation of returns, considering values between 15 and 25 days in increments of 5.

5.2.5 Sensitivity analysis: results

The heatmap of Figure 8 illustrates the gross profit of HS+ over the entire sample period as a function of the length of the rolling window volatility and the quantile of the volatilities' distribution. Interestingly, we obtain returns between 190.9% (scenario: Volatility Window: 76; Volatility Quantile: 0.74) and 290.1% (scenario: Volatility Window: 83; Volatility Quantile: 0.70), which consistently beat the B&H portfolio, constituting the best among the alternative benchmark strategies in Table 10. Furthermore, the strategy corresponding to the 80^{th} quantile threshold and 80-day EU ETS firms' volatilities that we used for the main analyses guarantees an intermediate level of performance, falling between the best- and worst-case scenarios. Therefore, we prudentially select it to further analyze the stability of our results based on the CUM RET hyper-parameter.

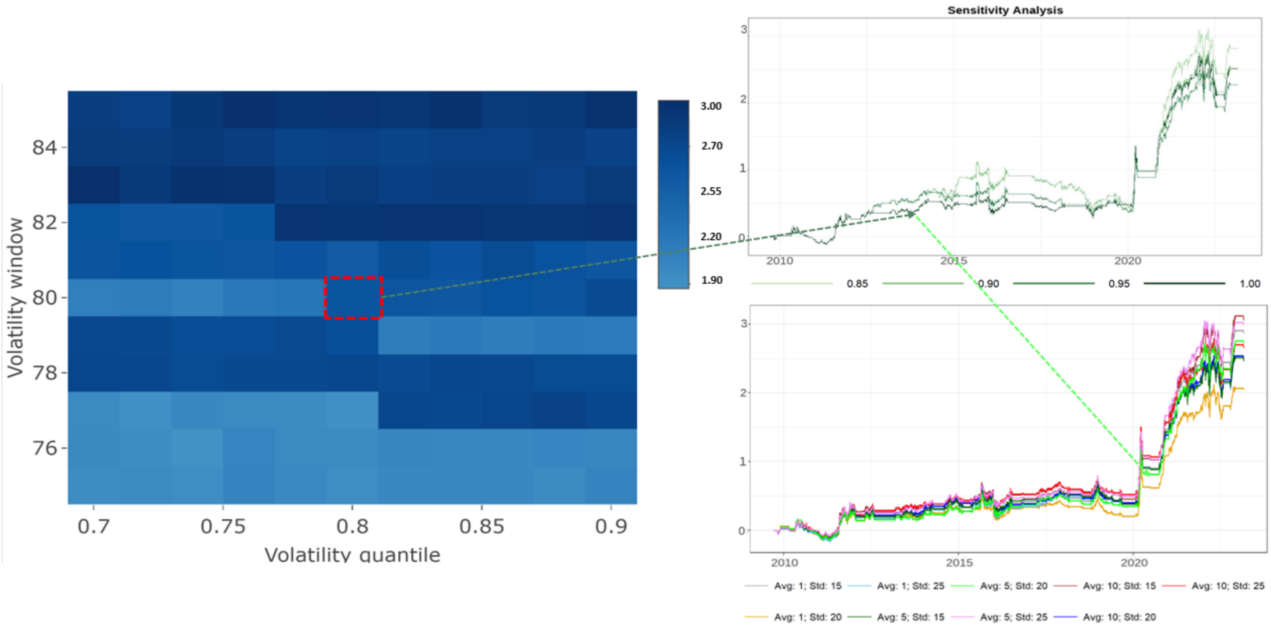


Figure 8: Sensitivity analysis. On the left, we present a heatmap of the gross return of HS+ as a function of the volatility quantile and the volatility window. HS+ consistently outperforms the buy-and-hold (B&H) strategy, achieving gross returns between 190.9% and 290.1% (average: 253.4%). The upper-right panel shows a sensitivity analysis of the cumulative return threshold, which serves as an exit condition for HS+. Entry and other exit parameters are fixed at the configuration highlighted by the red dashed rectangle in the heatmap (the 80^{th} quantile of the distribution of the previous 80 trading days' market volatilities). The dark green dashed arrow indicates the HS+ strategy selected for comparison against benchmarking strategies. The lower-right panel reports a sensitivity analysis on the averaging window for EU ETS firms' returns and the rolling window for the standard deviation of returns, while holding the other hyperparameters fixed (80^{th} quantile of the previous 80-day volatility distribution, CUM RET = 1). The light green dashed arrow marks the HS+ strategy chosen for benchmarking comparisons.

Given this choice, the upper-right panel of Figure 8 reports a sensitivity analysis of the exit threshold on the cumulative return of spillover. The results show that cumulative performances range from 226.6% (CUM RET = 0.95) to 280.9% (CUM RET = 0.85), consistently outperforming all alternative portfolios reported in Table 10. Our choice of the CUM RET hyperparameter in the main analysis yields a performance that lies comfortably between the best and worst outcomes. The lower-right panel of Figure 8 presents a sensitivity analysis on the averaging horizon for EU ETS firms' returns and the rolling window used to compute their return volatility. Even in this case, the hyperparameter selection adopted in the main analysis ensures a robust performance situated between the most favorable (308.3%) and least favorable outcomes (205.1%).

Overall, our proposed strategy HS+ is stable across a broad set of alternative values of the hyper-parameters characterizing our trading algorithm. This result highlights the good potential of a trading-based application that combines market volatility and market connectedness information to identify early phases of herding behaviors. For instance, EU ETS participants can refer to these strategies to manage energy-related risks that may undermine the correct market perception during periods of high uncertainty.

6 Conclusion

This paper analyzes the relationship between herding behavior and market connectedness within the perimeter of firms operating under the EU ETS, one of the main pillars of European climate policy. Firms are increasingly aware of the importance of signaling to investors their environmental commitments; however, market anomalies such as herding may limit access to relevant information and increase uncertainty regarding environmental performance. As a result, firms might become more reluctant to undertake long-term investments in cleaner technologies, reducing the cost-effectiveness of carbon abatement policies.

To examine herding behavior among EU ETS-listed firms, we extend the conventional CSAD model by incorporating spillover variation as an additional variable to explain investors' investment clustering, measured in terms of cross-sectional absolute deviation of returns. Using a sample of 345 firms over 2009–2023, we find that stronger connectedness in the energy commodities system, indicating a higher likelihood of spillover propagation, is associated with a reduction in the CSAD during periods of high market volatility, signaling intensified herding during distressed phases. Conversely, negative spillover variations (i.e., a reduction in connectedness) display the opposite pattern. When volatility is low or stable, connectedness exerts only a marginal influence on herding intensity.

Robustness checks confirm that these results are not driven by specific time windows or crisis episodes. Sectoral heterogeneity analysis further shows that energy firms exhibit the strongest herding intensity, while manufacturing firms display higher variability. This is consistent with the construction of our spillover index, which captures linkages across key energy commodities that directly influence the business activities of energy-intensive firms.

From an investor's perspective, we develop alternative investment strategies combining market volatility and spillover information to more effectively detect herding phases. Our strategies significantly outperform more standard portfolio approaches, such as a buy-and-hold, a minimum connectedness, and an equally weighted portfolio on the three market indices used to compute the CSAD. Our proposed approach can therefore more accurately identify phases of market instability and their duration, ultimately enhancing investors' portfolio decisions.

From a policymaker's perspective, our analysis shows how EU ETS-regulated firms tend to exhibit synchronized market dynamics during herding-like phases. Since it may be more difficult for investors to detect cross-sectional heterogeneity in these periods, this could weaken firms' incentives to invest in carbon abatement, ultimately undermining the effectiveness of the policy. Reducing uncertainty about firms' environmental outcomes may prompt investors to tilt their portfolios toward assets with stronger environmental profiles (Avramov et al., 2022). Improving the accessibility and credibility of this information would help maintain investor confidence and direct capital toward better environmentally performing firms, even in turbulent market conditions. Our results suggest that identifying herding behavior can provide market participants with valuable information about such collective dynamics, helping them to better interpret market signals and mitigate information losses (Philippas et al., 2021). This, in turn, can enhance market efficiency and support more effective policy design.

Finally, the sectoral heterogeneity in herding behavior underscores the importance of targeted regulatory measures. Energy firms are central within the EU ETS, being the only sector whose free allowance allocation is, in aggregate, below verified emissions (Chèze et al., 2020), likely due to cheaper abatement options and a lower risk of carbon leakage (Martin et al., 2014, Zaklan, 2023). If market behavior distortions alter their carbon abatement efforts, this may, in turn, also affect allowance trading volumes and the overall performance of the carbon market.

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