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Summary

We study the European Union's Emission Trading System (EU ETS) from a financial perspective. Using ARMA-eGARCH filtered volatilities, we first discuss the evolution of the volatility of EU ETS allowances' returns from 2008 to 2021. Second, we study the degree of co-movement and interdependence between the EU ETS returns' volatility and those of 37 large companies in industries subject to the System; to this end, we employ Wavelet Coherence and Volatility Spillovers Analyses. Despite spotting seasons of co-movement between volatilities in the markets under consideration, the market performances of the companies in our sample are not particularly responsive to the EU ETS dynamics, except for temporary seasons of interconnection in correspondence of relevant policy changes.

Keywords: EU Emission Trading System, volatility spillovers, wavelet coherence

JEL CLassification: C22, G11, Q58

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Financial implications of the EU Emission Trading System: an analysis of wavelet coherence and volatility spillovers

Pietro De Ponti* Matteo Romagnoli*

Abstract

We study the European Union's Emission Trading System (EU ETS) from a financial perspective. Using ARMA-eGARCH filtered volatilities, we first discuss the evolution of the volatility of EU ETS allowances' returns from 2008 to 2021. Second, we study the degree of co-movement and interdependence between the EU ETS returns' volatility and those of 37 large companies in industries subject to the System; to this end, we employ Wavelet Coherence and Volatility Spillovers Analyses. Despite spotting seasons of co-movement between volatilities in the markets under consideration, the market performances of the companies in our sample are not particularly responsive to the EU ETS dynamics, except for temporary seasons of interconnection in correspondence of relevant policy changes.

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1 Introduction

In recent years, the European Union has been at the forefront of the debate on climate and environmental issues, with the long-term objective to become the first greenhouse gas-neutral continent in the world.[1]

In this context, one of the key tool for cutting greenhouse gas (henceforth, GHG) emissions cost-effectively is the *European Trading System* (henceforth, EU ETS), the first and largest carbon market worldwide. Built as a *Cap and Trade* scheme, it sets a maximum

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[1]For legislative sources, see COM/2010/2020, COM/2018/773, COM/2019/640 final.

amount of GHG which can be emitted by installations covered by the system; within the cap, companies from high-polluting industries receive or buy emission allowances, which they can trade with one another as needed.

The EU ETS has been widely investigated in terms of its contribution to GHG emissions reduction and to low-carbon innovations. On the other hand, there are limited contributions addressing its financial and asset management implications. In this regard, to fill this gap, we study whether and how the volatility of EU ETS allowances' returns relates to the volatility of the returns of companies under the System.

Volatility captures uncertainty and risk in an asset; hence, when the returns volatility of EU ETS allowances increases, they become riskier assets as their price is less predictable and subject to larger oscillations. Therefore, volatility on the EU ETS market could spill over onto the demand side: companies subject to the System face greater uncertainty, as they require allowances to operate. In turn, they could be perceived as riskier at the eyes of investors.

To test these intuitions, first, we discuss the evolution of the EU ETS returns volatility over the period 2008-2021, using an ARMA-eGARCH model for filtered volatilities. Second, we investigate the co-movement between the volatility in the EU ETS returns and those of a sample of 37 large companies, operating in four of the main industries subject to the System; to this end, we employ Wavelet Coherence Analysis (henceforth, WCA). Third, using the Diebold and Yilmaz (2009, 2012, 2014, 2015) (henceforth, DY) Spillovers frameworks, we test whether and how volatility from the EU ETS returns spills over onto the returns volatilities of the firms in our sample.

Regarding the pattern of the EU ETS returns volatility, our results suggest the series is generally persistent and presents areas of clustering; estimates of the ARMA-eGARCH specification show the presence of fat tails and leverage effects. Evidence from the WCA points out regions of significant co-movement in the medium-run between volatilities in the EU ETS' and the companies' returns; however, they are few and limited to relatively small time periods. The DY Spillovers analysis highlights several significant patterns. Overall, the EU ETS returns volatility series is a net receiver of spillovers across all industries. It is a net contributor of volatility only at early stages of our time span (for all industries), as well as in correspondence of a major policy change over the period 2012-2014 (for three out of four industries); the outbreak of the Covid-19 pandemic translates into an increases of volatility spillovers both from and to the EU ETS, with the latter effect exceeding the former.

Our evidence suggests that, on balance, uncertainty in the EU ETS returns does not reflect on the uncertainty in the stock returns of firms subject to the System. There are few exceptions, in correspondence of relevant EU ETS policy changes or periods of high uncertainty; investors, however, seem not to be affected by the volatility dynamics of the EU ETS returns in their investment decisions.

We contribute to the existing literature by integrating an ARMA-eGARCH specification with WCA and DY Spillovers frameworks, to study the financial implications of uncertainty in the EU ETS. This allows us to provide a comprehensive analysis of the dynamics of the EU ETS returns volatility series which, to our knowledge, has not been investigated yet using such methodologies. In addition, contrary to previous studies on the link between the System and the stock market, we do not focus on the energy sector, only, but include firms from different industries in our sample, as well.

We proceed as follows. Section 2 is devoted to reviewing related literature. In Section 3, we present our data. In Section 4, we describe the methodological approaches employed. In Section 5, we discuss results. Conclusive remarks follow in Section 7.

2 Literature Review

The EU ETS is a market for carbon emissions, operational since 2005 in all EU countries (plus Iceland, Liechtenstein and Norway) and covering a variety of GHG emissions and industries.[2]

It is based on a *Cap and Trade* emission trading scheme (Schmalensee and Stavins, 2017). A maximum amount of GHG emissions is set for the industries covered by the System (the *Cap*), that is decreasing over time to entail a reduction of total emissions. Since it is designed to cover sizeable installations, each firm operating large enough plants receives an initial amount of emission allowances or permits. Firms are allowed to buy and sell permits as needed (the *Trade*), giving rise to a market for emissions allowances which, in turn, results in *pricing* GHG emissions.

Permits are allocated via a *partial auctioning and partial free* mechanism, based on each industry's exposure to international trade (Verbruggen et al., 2019).[3]

The System's earliest stages were characterized by an over-allocation of free emission allowances. At the end of 2012, the second phase of the EU ETS (*Phase 2*) gave way to the third (*Phase 3*); this major policy change (henceforth referred to as the *Phase 2-Phase 3* passage) entailed the inclusion of additional sectors under the system, and a substantial decrease in the share of permits allocated through free auctioning.

Among industries under the EU ETS, the energy sector deserves a special mention. In light of its low exposition to international trade and its high contribution to overall GHG emissions, firms operating in the energy sector have enjoyed comparatively less free-auctioning with respect to their counterparts (Verbruggen et al., 2019). This being the

[2]More specifically, the EU ETS targets the following emissions and industries: (a) carbon dioxide (CO_2), generated from energy industries, commercial aviation, other energy-intensive industry sectors (including oil refineries, steel works and production of iron, aluminium, metals, cement, lime, glass, ceramics, pulp, paper, cardboard, acids and bulk organic chemicals); (b) nitrous oxide (N_2O), generated from the production of nitric, adipic and glyoxylic acids and glyoxal; (c) perfluorocarbons (PFCs), generated from aluminium production.

[3]In principle, the emission-intensive trade-exposed sectors are endowed with free permits by the EU, while energy-intensive non-trade-exposed sectors must bridge their gaps in permits via allocation auctions or purchase transactions.

case, one could expect volatility in the energy stock market to be more sensitive than other industries' to volatility in the System.

The overall efficacy of the EU ETS in reducing GHG emissions has been widely investigated. Among scholars, opinions on its desirability and effectiveness are not univocal: different studies reach substantially different conclusions, ranging from strong support for the instrument, to being conditionally in favor of its use, to rejecting it as the preferred climate policy choice (Pearse and Böhm, 2014; Gollier and Tirole, 2015; Verbruggen et al., 2019; Woerdman and Nentjes, 2019).

Another relevant topic in this literature is the ability of the System to foster low-carbon innovations (Schmidt et al., 2012; Martin et al., 2013; Löfgren et al., 2014; Borghesi et al., 2015; Calel and Dechezleprêtre, 2016; Bel and Joseph, 2018; Calel, 2020). Teixidó et al. (2019) finds two robust evidence in this line of research. First, permits' free allocation has negative effects on low-carbon investments during the EU ETS' *Phase 1* and *2* (2005–2007 and 2008–2012). Second, the EU ETS appears to have been more effective in stimulating innovation in low-carbon technologies, rather than their adoption.

We take a different perspective and study EU ETS from a financial and asset management standpoint. Rather than evaluating the its efficacy as a climate policy, our aim is to investigate the evolution of uncertainty in its allowances' returns and its relevance for investors of firms subject to the System.

While the financial and asset management implications of the EU ETS are relatively less studied in the literature, there are several papers taking this approach.

Wen et al. (2020) uses a nonlinear auto-regressive distributed lag model to investigate the relationship between carbon ETS and stock market in China. They provide evidence suggesting that increases in carbon price have a negative effect on stock prices; moreover, the negative effect of increases in carbon price on stock prices is larger than the positive effect observed when carbon price decreases. Zeng et al. (2021) studies the volatility spillover effect between the EU ETS allowances and certified emissions reduction (CER) markets; results suggest an asymmetric volatility spillover effect exists between the former and the latter (i.e. EU ETS allowances spillovers *to* CER markets are larger than vice-versa).

Other works provide evidence that investors may keep an eye on changes in the price of ETS allowances and/or meaningful policy announcement related to carbon emissions trading schemes. Moreno and da Silva (2016) employs a panel data econometric approach to investigate correlation between changes in the daily price of EU ETS allowances and stock returns of sectors subject to the System in Spain. The authors find a positive correlation at early stages of the EU ETS, which becomes negative after the *Phase 2-Phase 3* passage. Chapple et al. (2013) shows the most carbon-intensive firms on the Australian Security Exchange experienced a negative and statistically significant decrease in market value with respect to other companies, after the Australian Government announcement on the intention to introduce a national Emissions Trading Scheme in March 2008.

A piece of literature that is close to ours is Ji et al. (2019), investigating the connectedness between carbon price returns and the stock returns of 18 top European electricity companies. The authors argue the EU ETS behaves as information recipient, absorbing different degrees of information spillovers. This seems to suggest investors' decisions on the stock market are not particularly driven by EU ETS' market dynamics; rather, the correlation between EU ETS' and electricity companies' returns could be due to the fact that both are affected by firms' performances. Similar results are presented in Li et al. (2020) with regards to the spillovers dynamics between the national carbon trading scheme and the power industry in China. However, they also provide evidence of occasional and temporary positive *net* spillovers *from* the Chinese carbon emission market *to* the stock market.

In this context, a lot remains to be understood in terms of the financial implications of the EU ETS. Thanks to the different methodologies employed, we believe our work can be useful to that aim.

We believe our paper's contribution to the literature is threefold. First, we describe the evolution of uncertainty in the EU ETS market, using an ARMA-eGARCH specification to extract conditional volatility. Second, we investigate the correlation and the interconnectedness between volatility in the EU ETS and in the stock returns of firms under the System; we do this by integrating WCA with the DY Spillovers framework. Third, we expand the analysis to industries other than energy generation.

3 Data

To compute the EU ETS carbon market returns, we use the EXC EUA settle futures price, based on raw data from ICE and obtained from Nasdaq Data Link.[4]

Stock market returns are calculated for ten European Energy companies, nine Airways, seven Cement production companies and eleven Chemicals production companies, using daily adjusted primary stock prices from Datastream. These companies are:

- Energy: Edison (Italy)[5], Électricité de France (henceforth, EDF; France), EnBW (Germany), Enel (Italy), E.ON (Germany), Iberdrola (Spain), RWE (Germany), Scottish and Southern Energy (henceforth, SSE; Scotland), Fortum (Finland) and Verbund (Austria);
- Airways: Air France-KLM (France and Netherlands), easyJet (Great Britain), Finnair (Finland), Ryanair (Republic of Ireland), Lufthansa (Germany), Norwegian Air Shuttle (Norway), SAS (Denmark, Norway and Sweden), Turkish Airlines (Turkey) and Aeroflot (Russia);[6]

[4]Source: https://data.nasdaq.com/data/CHRIS/ICE_C1-ecx-eua-futures-continuous-contract-1-c1-front-month.
[5]In 2012, Edison was entirely acquired by EDF.
[6]Norwegian Air Shuttle and SAS are included in light of the fact that the EU ETS applies to Norway, as well.

- Cement production: Buzzi Unicem (Italy), HeidelbergCement (Germany), Lafarge-Holcim (France and Switzerland), CRH (Republic of Ireland), Vicat (France), OYAK (Turkey), Cementir (Italy);
- Chemicals production: BASF (Germany), Bayer (Germany), Solvay (Belgium), DSM (Netherlands), Air Liquide (France), Umicore (Belgium), Arkema (France), Lanxess (Germany), Linde (Germany), Yara (Norway), AkzoNobel (Netherlands).

Note that commercial aviation has been subject to the EU ETS carbon emission requirements from 2012. However, the discussion on its addition to the system dated back to 2008, hence the inclusion of airways in our sample of representative companies.[7]

All prices are expressed in Euros and range between April, 8th, 2008 and January, 26st, 2021.

Missing values in the EU ETS carbon market price time series over April-May 2011 led to the omission of such observations. The final sample consists in 3,264 observations for each variable of interest.

4 Methodological approaches

To address the relationship of interest, three different methodologies are used.

First, we extract conditional volatilities, using an ARMA-eGARCH model for filtered volatilities. Then, these are used as inputs in the WCA and DY Spillovers analysis.

The analysis is carried out by industry. We refer to them as the *Energy* sub-sample, the *Airways* sub-sample, the *Cement* sub-sample and the *Chemicals* sub-sample.

The analysis of the relationship between the returns volatilities of the EU ETS and the representative companies in the sample is carried out at the industry level: we will refer to the different EU ETS-industry sub-samples as the *Energy* sub-sample, the *Airways* sub-sample, the *Cement* sub-sample and the *Chemicals* sub-sample.

4.1 Extracting conditional volatility

Unlike the traditional body of literature, we follow Engle (2001) and Dahl et al. (2020) to extract returns conditional volatility, using ARMA-GARCH models for filtered volatilities.

Returns series are often characterized by issues such as volatility clustering, serial correlation, heteroskedasticity, leverage effects and fat tails: in light of the ability of GARCH-type specifications to capture these properties, their choice appears appropriate (Cont, 2001).

We select four suitable ARMA-GARCH models to extract conditional volatility from the returns series of our sub-samples: for each, we select the model that produces the lowest AIC.

[7]For legislative sources, see Directive 2008/101/EC of the European Parliament and of the Council of 19 November 2008.

As far as the GARCH component is concerned, we employ an eGARCH model in all specifications: not only the eGARCH model is more flexible than the standard GARCH model, but also assumes that negative and positive shocks have asymmetric effects on conditional volatility (Dahl et al., 2020).

According to our estimates, the most suitable models are the following:

- ARMA(0,1)-eGARCH(1,1) with errors distributed as a Skew Student's t-distribution, for the Energy sub-sample;
- ARMA(1,1)-eGARCH(1,1) with errors distributed as a Skew Student's t-distribution, for the *Airways* sub-sample;
- ARMA(1,1)-eGARCH(1,1) with errors distributed as a Student's t-distribution, for the *Cement* sub-sample;
- ARMA(0,1)-eGARCH(1,1) with errors distributed as a Skew Student's t-distribution, for the *Chemicals* sub-sample.

4.2 Wavelet Coherence Analysis (WCA)

WCA is a technique allowing to analyse both time and frequency dimensions of data, jointly. Before introducing WCA, it is necessary to briefly discuss the definitions of wavelet, continuous wavelet transform and cross-wavelet transform.

A *wavelet* is a function with zero mean, defined with respect to two dimensions, i.e. time and frequency.

By applying a wavelet as a low and high-pass filter to a given uni-dimensional time series, it is possible to decompose it into a bi-dimensional time-frequency sphere. This procedure is referred to as *continuous wavelet transform*.

Intuitively, these low and high-pass filters are obtained by stretching and shortening the so-called *mother wavelet*. A commonly used example of *mother wavelet* is the Morlet wavelet, defined as:

$$\psi_0(\eta) = \pi^{-1/4} e^{i\omega_0\eta} e^{-\frac{1}{2}\eta^2}, \tag{1}$$

where η is the dimensionless time parameter, ω_0 is dimensionless frequency and $\pi^{-1/4}$ is a normalization term.[8]

When using wavelets for feature extraction purposes, the Morlet wavelet is known to be a good choice, as it provides a good balance between time and frequency localization (Grinsted et al., 2004).[9] This being the case, we adopt it in the remainder of the paper.

[8] A dimensionless quantity is a quantity to which no physical dimension is assigned. The conceptual representation of discrete time signals relies on the notion of dimensionless time, indicated simply by an integer index. Similarly, dimensionless frequency is not measured in hertz but using integers. For a reference, see Prandoni and Vetterli (2008).

[9] Feature extraction refers to the process of transforming raw data into numerical features, which can be processed without losing the information in the original dataset.

Following Grinsted et al., (2004), the continuous wavelet transform W_t of a time series x_n ($n = 1, ..., N$) with uniform time steps δ_t can be written as:

$$W_n^X(s) = \sqrt{\frac{\delta t}{s}} \sum_{n'=1}^{N} x_{n'} \psi_0 [(n' - n)\frac{\delta t}{s}], \tag{2}$$

Given two time series X and Y with continuous wavelet transforms $W_n^X(s)$ and $W_n^Y(s)$, one can define the *cross-wavelet transform* as $W^{XY} = W^X W^Y*$, where W^Y* is the complex conjugates of W^Y (Torrence and Compo 1998).

Wavelet Coherence Analysis allows us to measure the coherence of a cross-wavelet transform in the time-frequency space. We write the wavelet coherence of two time series as in Torrence and Webster (1998) and Grinsted et al. (2004)

$$R_n^2(s) = \frac{|S(s^{-1} W_n^{XY}(s))|^2}{S(s^{-1}|W_n^X(s)|^2) \cdot S(s^{-1}|W_n^Y(s)|^2)}, \tag{3}$$

where S is a smoothing operator.[10] Quoting from Grinsted et al. (2004), «*this definition closely resembles that of a traditional correlation coefficient, and it is useful to think of the wavelet coherence as a localized correlation coefficient in time frequency space*» (p. 564).

The WCA approach uses information coming from leads and lags of a specific observation to estimate whether there is co-movement between two series. This being the case, interpretation of the results at the edges can be misleading. The area in which these edge effects cannot be ignored is called *cone of influence* (Grinsted et al., 2004). The statistical significance level of the wavelet coherence is estimated using Monte Carlo methods for each scale using values outside the cone of influence.[11]

An advantage of this methodology is that it is model-free, that is, it does not impose any prerequisite or condition on how the series should be: this ultimately translates in fewer assumptions and higher flexibility, both of which are obviously good.

WCA seems a perfect methodological complement to our analysis for two reasons. On the one hand, decomposing a series in its short-run and long-run components permits to gather information from low to high frequencies fluctuations and can reveal relationships which are not obvious in aggregate data. DY Spillovers analysis makes use of aggregate data, only; by adding the frequency dimension, WCA not only allows to assess whether EU ETS' and companies stock returns' volatility are co-moving, but also if their co-movement occurs at low or high time horizons.

On the other hand, results from the EU ETS conditional volatility analysis can be used to inform our expectations on the outcomes of WCA, thus avoiding the blind application of such methodology as suggested by Grinsted et al. (2004).

[10] For a technical discussion on S, see Torrence and Webster (1998) and Grinsted et al. (2004).

[11] For additional technical details, see Grinsted et al. (2004).

4.3 Volatility spillovers

From an intuitive standpoint, volatility spillovers measure the extent to which the volatility of a given stock's return spills over onto other markets or stocks. In other words, volatility spillovers measure whether and how changes in the uncertainty regarding a given asset affects or is affected by the uncertainty of another asset. Studying volatility spillovers may contribute understanding the degree of interdependence and connectedness of different markets, and help investors shaping their portfolios accordingly.

The methodology we adopt to study spillovers finds its roots in Diebold and Yilmaz (2009, 2012, 2014, 2015) and relies on the error variance decomposition of a *generalized* vector autoregressive framework (Koop et al., 1996; Pesaran and Shin, 1998) (KPPS).

Contrary to more common approaches using impulse response functions with Cholesky factor decomposition, the proposed framework has the advantage of eliminating order dependence in the obtained results and accounting for directional spillovers.

We start from a generalized vector autoregressive (VAR) model defined as follows. Consider a set of N covariance-stationary variables represented as the following VAR(p) model

$$x_t = \sum_{i=1}^{p} \phi_i x_{t-i} + \epsilon_t \tag{4}$$

where $\epsilon \sim (0, \Sigma)$ is a vector of independently and identically distributed disturbances. Its moving average representation is

$$x_t = \sum_{i=0}^{\infty} A_i \epsilon_{t-i} \tag{5}$$

where the $N \times N$ coefficient matrices A_i obey the recursion $A_i = \phi_1 A_{i-1} + \phi_2 A_{i-2} + \dots \phi_p A_{i-p}$, with A_0 being an $N \times N$ identity matrix and with $A_i = 0$ for $i < 0$.

The fractions of the H-step-ahead error variances in forecasting x_i that are due to shocks to x_i itself are defined as *own variance shares*, while the fractions of the H-step-ahead error variances in forecasting x_i that are due to shocks to x_j $(i, j = 1, 2, ..., N, i \neq j)$ are defined as *spillovers*. The KPPS H-step-ahead generalized forecast error variance decompositions is

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \sum e_j)^2}{\sum_{h=0}^{H-1} e_i' A_h \sum A_h' e_j)^2}, \tag{6}$$

where Σ is the variance matrix for the error vector ϵ, σ_{jj} is the standard deviation of the error term for the j-th equation, and e_i is the selection vector, with one as the i-th element and zeros otherwise. Note that, due to the generalized approach in the VAR, the shocks to each variable are not orthogonal: hence, the row sum of the elements of the variance decomposition table is not necessarily equal to one. To circumvent this issue, each entry of the variance decomposition matrix is normalized by the row sum as:

$$\tilde{\theta}^g_{ij}(H) = \frac{\theta^g_{ij}(H)}{\sum_{j=1}^{N} \theta^g_{ij}(H)}, \tag{7}$$

The volatility spillover index is, therefore, constructed as

$$S^g(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}^g_{ij}(H)}{N} \times 100, \tag{8}$$

It quantifies the contribution of spillovers of volatility shocks across all series of stock returns to the total forecast error variance.

Thanks to the generalized VAR approach, it is possible to learn about the direction of volatility spillovers across different assets. In particular, the directional volatility spillovers received by asset i from all other assets j are measured as

$$S^g_{i\cdot}(H) = \frac{\sum_{\substack{j=1 \\ J \neq i}}^{N} \tilde{\theta}^g_{ij}(H)}{N} \times 100, \tag{9}$$

Similarly, the directional volatility spillovers transmitted by asset i to all other assets j are measured as:

$$S^g_{\cdot i}(H) = \frac{\sum_{\substack{j=1 \\ J \neq i}}^{N} \tilde{\theta}^g_{ji}(H)}{N} \times 100, \tag{10}$$

Finally. the *Net* volatility spillovers are defined as the difference between the shocks transmitted to and those received from other assets. To be more precise, the *Net* spillovers from asset i to all other assets j can be computed as:

$$S^g(H) = S^g_{\cdot i}(H) - S^g_{i\cdot}(H), \tag{11}$$

5 Empirical Analysis and Results

5.1 Estimates of the EU ETS returns volatility

We rely on the AIC information criterion to choose the optimal ARMA-eGARCH model for extracting the conditional volatility of the EU ETS returns series. We select an ARMA(0,1)-eGARCH(1,1) specification, with errors distributed as a Student's t-distribution.[12]

Results are described in Table 1. In the estimates of the Mean Equation, the lagged moving average parameter $MA(1)$ is negative and significant at the 10% level, suggesting past values of the error term might affect current returns. Parameters from the GARCH equation present higher levels of statistical significance, being all significant at the 1% level. Estimates for the ARCH component (α) and the GARCH component (β) indicate

[12] Alternative specifications among those presented in Section 5 lead essentially to the same results.

high persistence in conditional volatility for the underlying series. The term capturing the presence of leverage effect (σ) confirms asymmetric impact of bad and good news on EU ETS returns conditional volatility while the *Student-df* parameter signals that fat tails and the potential for tail dependence characterize the distributions of the EU ETS returns series.

The last three rows of Table 1 presents model diagnostic tests. In regard to the ARCH LM Test and the Weighted Ljung Box Test on standardized squared residuals, we can not reject the null hypothesis of no conditional heteroskedasticity. The Weighted Ljung Box Test on standardized residuals does not allow for the rejection of the null hypothesis of no serial correlation. However, their autocorrelation functions illustrate that serial correlation is not a big issue in the proposed model (see Figure A.1 and A.2 in the Appendix).

Figure 1 plots the EU ETS allowances' returns during the period of interest. Figure 2, instead, plots the estimated volatility of EU ETS returns.

[FIGURES 1, 2 APPROXIMATELY HERE]

Returns are particularly volatile at the beginning of the sample and around 2012-2013. Afterwards, their oscillation decreases substantially and remains low throughout 2015. A period of relatively high volatility starts in 2016, following a sudden spike. Similar high spikes can be observed in 2018 and 2020.

The increase in EU ETS returns volatility emerging between 2012 and 2013 is likely to be due to the aforementioned *Phase 2-Phase 3* passage, which entailed a substantial decrease in the share of permits allocated through free auctioning. In the rest of the time span, various potentially relevant events occurred. Nevertheless, their contribution to the EU ETS volatility dynamics is less unequivocal. Among the others, we recall policy changes such as the EU ETS *Back-loading* (2014-2016)[13], the ratification of the United Nations' *Sustainability Development Goals* and the adoption of the *Paris Agreement* (both in late 2015). Finally, the increase in the price of EU ETS allowances starting in 2018 and the outbreak of the Covid-19 pandemic in 2020 are also likely to have played a role in increasing uncertainty on the European carbon market.[14]

A priori, if EU ETS returns volatility spills over onto the stock market, one would think the effect to be stronger in times of high EU ETS volatility: in fact, it seems legit to expect extreme manifestations of uncertainty are more likely to affect investors' behaviour and their decision-making process. In light of our previous considerations, this provides the following testable prediction: if EU ETS returns volatility spills over onto the companies' stock prices under analysis, spillovers are expected to be concentrated in correspondence of cluster of high EU ETS returns volatility (i.e. in correspondence of the *Phase 2-Phase 3* passage, in late 2015-early 2016 and in 2018).

[13]Over the period 2014- 2016, the planned amount of allowances to be auctioned was substantially cut as a short-term fix for the oversupply of permits. Although the EU ETS allowances supply was sensibly reduced, the surplus of allowances in the EU ETS market in 2015 still amounted to 1.78 billion permits.

[14]See Figure A.3 in the Appendix for the series of EU ETS allowances futures prices.

5.2 Wavelet Coherence Analysis (WCA)

Common trends emerging across the sample of representative firms are highlighted in Figure 3, representing wavelet coherence between the EU ETS returns volatility series and an index of returns volatility computed for each industry.[15]

[FIGURE 3 APPROXIMATELY HERE]

Overall, WCA highlights limited co-movement between volatility in the EU ETS and in the stock market.

Co-movement regularities across all sub-samples are present in correspondence of 2012-2014, 2016 and 2020, as well as at the beginning of the time span considered (albeit milder). These results are coherent with the high volatility windows discussed in Section 5.1, with regards to the EU ETS returns volatility.

The series' decomposition in short-run and long-run components highlights that, whenever co-movement emerges, it does so in the the medium run only, that is, between fortnight and two-month periods. While minor, yet significant co-movements can be spotted for higher frequencies, no trace of correlation is present at low frequencies.

Results are generally not indicative on which series is leading the co-movement, with the exception of the correlations around 2020. In this case, we clearly see that the EU ETS returns volatility lags the stocks returns volatilities in all industries.

As noted by Grinsted et al. (2004), consistent co-movement between time series can be suggestive of causal relationships. In light of the results presented so far, we investigate whether volatility in the EU ETS reflects on the returns volatility of the companies under analysis, especially in correspondence of the seasons of high EU ETS volatility and EU ETS-stocks co-movement.

5.3 Volatility Spillovers

Static volatility spillovers

The static spillovers analysis provides an overview of overall connectedness dynamics between the underlying assets.

Table 2 presents static volatility spillovers regarding the EU ETS return volatility as it emerges from the analysis in each industry under consideration.[16]

[TABLE 2 APPROXIMATELY HERE]

To spillovers represent the gross directional volatility spillovers contributions going from the EU ETS volatility *to* the stock returns volatilities of the companies in each industry.

[15]These indexes are computed as the average of stock returns for companies operating in the same industry; this procedure result in four indexes. Detailed results of the WCA by couples are available upon request.

[16]Comprehensive static spillovers tables, showing all the possible bivariate relations of directional static spillovers for each sub-samples, are available in the Appendix (Tables A.1, A.2, A.3, A.4).

Vice versa, *From* spillovers are the gross directional volatility spillovers transmitted in the opposite direction. The difference between *From* and *To* spillovers are the *Net* returns spillovers, indicating whether the EU ETS is a net transmitter or receiver of volatility shocks.

To account for structural variation, we distinguish between different time periods. Column (1) refers to the whole period under analysis (8Apr2008 -26Jan2021); column (2) refers to the EU ETS' *Phase 2* (8Apr2008 - 31Dec2012); column (3) refers to the EU ETS' *Phase 3*, before the Covid-19 pandemic outbreak (1Jan2013 - 31Dec2019); column (4) refers to the EU ETS' *Phase 3*, including the Covid-19 pandemic outbreak (1Jan2013 - 26Jan2021).[17]

As far as the EU ETS volatility is concerned, a few considerations are in turn.

First, the EU ETS is always a net receiver of volatility spillovers, the only exception being the *Energy* sub-sample under *Phase 3*, in line with the expectations discussed in Section 2.

Second, comparing columns (2) and (3), moving from *Phase 2* to *Phase 3* entails an increase in the System's *Net* spillovers in three out of four industries. This is not the case for the *Airways* sub-sample, where the EU ETS consolidates its position as a volatility spillovers recipient.

Third, column (4) illustrates extending the time period to include the Covid-19 pandemic outbreak entails a significant drop in the EU ETS *Net* spillovers. This is consistent with the evidence provided by previous sections, that is, the EU ETS volatility series lags the volatility patterns of the companies' stock returns around 2020.

These preliminary results suggest that uncertainty tends to flow from the stock market to the EU ETS, rather than vice versa.

Dynamic volatility spillovers

Static spillovers are unable to highlight whether and how specific events in time or periods of turmoil affect the direction and the intensity of connectedness between the markets of interest.

As discussed in Section 5.1, volatility in the EU ETS is clustered around specific time periods and follows a very heterogeneous pattern. This being the case, the loss of the time dimension in the static spillovers analysis is particularly costly and can lead to incomplete results. The analysis of dynamic volatility spillovers deepens the preliminary intuitions developed in the previous section, by considering their evolution in time.

[FIGURES 4, 5, 6, 7 APPROXIMATELY HERE]

[17]The increase in stock price volatility entailed by the Covid-19 global pandemic is well documented (Baker et al., 2020; Bai et al., 2021). We believe it might be appropriate to present results both with and without the pandemic outbreak.

Figures 4 to 7 present *To*, *From* and *Net* dynamic spillovers regarding the EU ETS return volatility, as it emerges from the analysis in each industry under consideration.[18]

Some common features emerge from the analysis.

First, for all industries under consideration, results from previous sections on the EU ETS *Net* volatility spillovers being low and mainly negative are confirmed.

Second, results suggest the EU ETS is a net contributor of volatility in the early stages of the time span, in correspondence to periods of economic turmoil (i.e. the global financial crisis and European debt crisis). Similar considerations hold for the 2012-2013 period, with the exception of the *Chemicals* sub-sample (i.e. in correspondence of the *Phase 2-Phase 3* passage).

Third, the EU ETS returns volatility spike and the WCA co-movement spotted in previous sections around 2016 do not translate to a period of particularly high *To* EU ETS spillovers, nor positive *Net* EU ETS spillovers.

Fourth, significant increases in *From* EU ETS spillovers occur in correspondence of the Covid-19 pandemic outbreak in all industries. This is highly consistent with the evidence provided by the WCA (see Figure 3), and translates in strongly negative EU ETS *Net* spillovers at the end of the time span.

6 Conclusion

In this paper, we study the European Union's EU ETS from a financial perspective.

First, using an ARMA-eGARCH model for filtered volatilities, we investigate the pattern of the EU ETS returns volatility over the period 2008-2021. Second, we employ WCA to explore the correlation across time and frequency between the volatility in the EU ETS and the returns volatilities of a sample of 37 large companies, operating in industries subject to the system (i.e. *Energy*, *Airways*, *Cement* production and *Chemicals*). Lastly, we apply the DY Spillovers framework to analyse whether and how volatility from the EU ETS returns spills over onto the returns volatilities of the firms in our sample.

Overall, our results suggest that volatility in the returns of EU ETS allowances is clustered, fat-tailed and characterized by leverage effects. In addition, volatilities in the EU ETS and in the stock market share limited seasons of co-movement; when correlation is observed, it occurs at medium frequencies, for moderately short duration and when uncertainty in the EU ETS is relatively high. We further investigate the EU ETS-stock market co-movement via DY Spillovers analysis. Results suggests that uncertainty in the EU ETS rarely spills over the stock returns volatility of firms under the EU ETS, which is generally a net receiver of volatility. We observe positive *Net* volatility spillovers from the EU ETS at the beginning of our sample and in correspondence of the EU ETS' *Phase*

[18] Comprehensive dynamic spillovers plots, showing the *Net* spillovers for each company and sub-sample, are available in the Appendix (Figures A.4, A.5, A.6, A.7).

2-Phase 3 passage; on the contrary, the EU ETS becomes a net receiver of volatility after the outbreak of the Covid-19 pandemic.

On balance, uncertainty in the EU ETS returns does not translate to uncertainty in the stock returns of firms subject to the system. Aside from few exceptions, investors seem not to be affected by the volatility dynamics of the EU ETS returns in their investment decisions.

According to the European Commission, the EU ETS is bound to play a major role in the attempt to achieve carbon neutrality. In light of this, we believe the contribution of our results is two-fold.

On the one hand, the evidence we provide may interest investors, investment funds and asset managers. Quoting from the statement from the President of the European Commissioner, Ursula von der Leyen, on delivering the European Green Deal, «*our existing Emissions Trading System has already helped significantly to reduce emissions in industry and in power generation. So we will strengthen the existing system in these sectors.*». Therefore, it is likely that further major policy changes will affect the EU ETS in the future, giving rise to potential volatility spillovers from EU ETS onto the stock markets, hence affecting the sectors constrained by this measure.

On the other hand, we show the System's ability to affect investors behaviour is marginal. This must be taken into account by policy-makers when designing the new steps of the EU ETS.

[18] Source: https://ec.europa.eu/commission/presscorner/detail/en/statement_21_3701.

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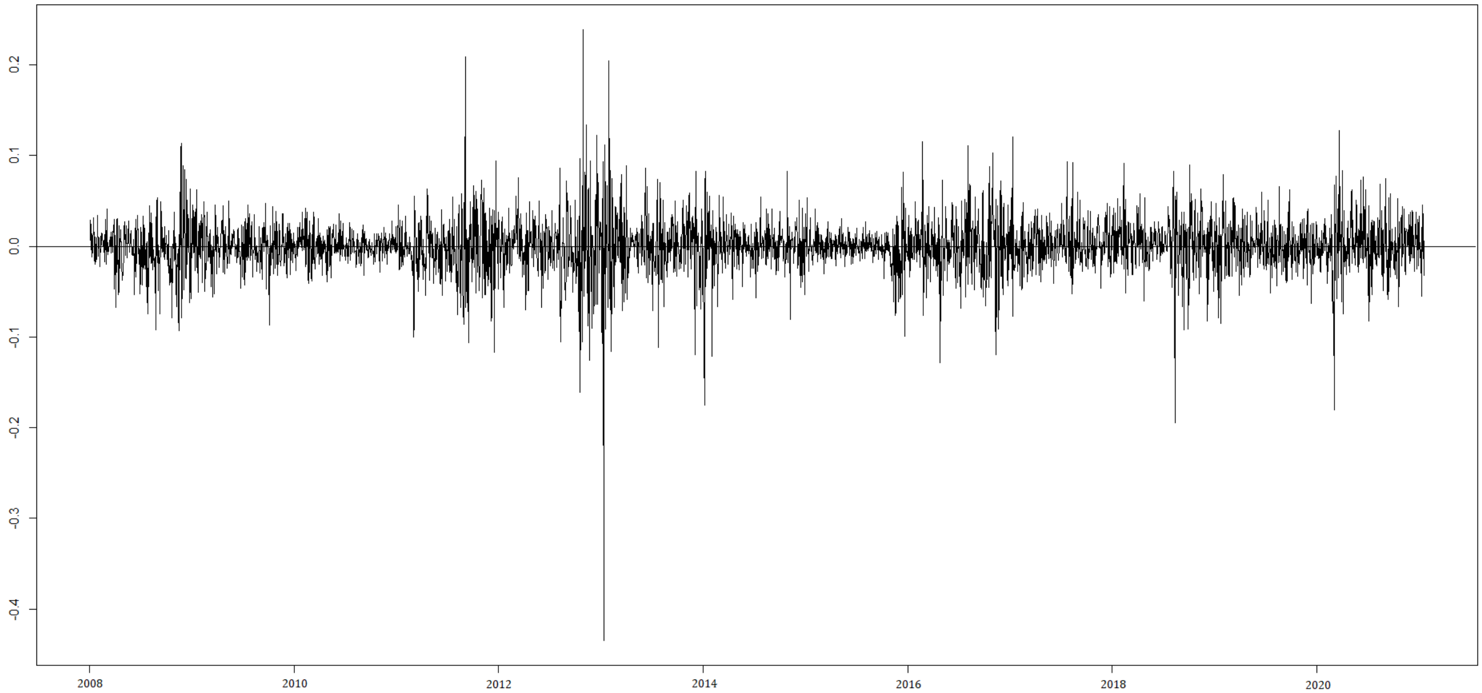
Tables and Figures

TABLE 1: GARCH Estimates for the EU ETS returns series

Mean Equation Estimates	
Const.	0.0005
	(0.0004)
MA(1)	-0.0339[a]
	(0.0184)
Garch Process Estimates	
Const. (Ω)	-0.1597[c]
	(0.0230)
ARCH (α)	-0.0421[c]
	(0.0121)
GARCH (β)	0.9780[c]
	(0.0031)
Leverage (σ)	0.2150[c]
	(0.0223)
Student-df	5.6595[c]
	(0.5401)
Log(L)	7284.215
WLB Test on Std. Res. [5]	0.0004
WLB Test on Std. Sq. Res. [5]	0.1359
ARCH LM Tests [5]	0.4450

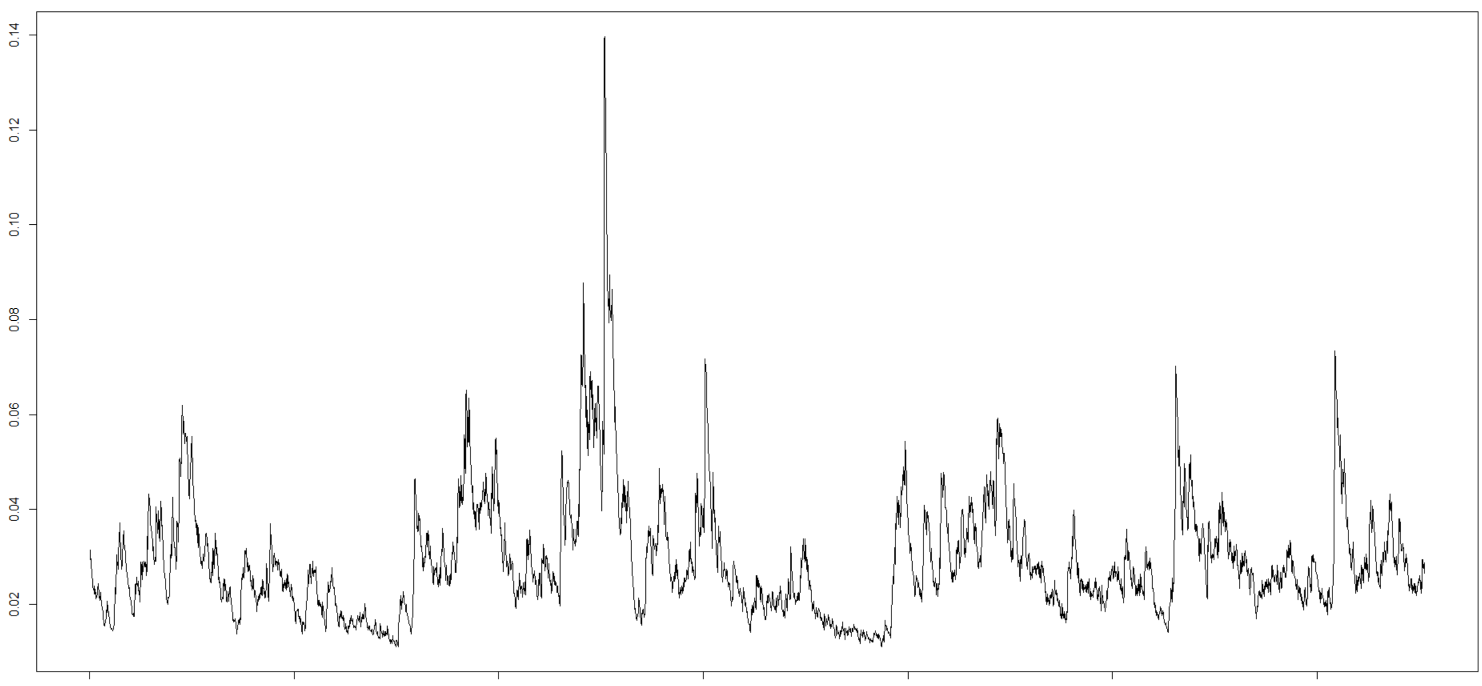
Notes: This table presents the estimates of an ARMA(0-1)eGARCH(1,1) model for the EU ETS return series. Standard errors are presented in parenthesis. The last three rows presents p-values from the Weighted Ljung-Box (WLB) Test on Standardised Residuals, the Weighted Ljung-Box Test on Standardised Squared Residuals and the Weighted ARCH LM Tests for 5 lags. *a* indicates significance at 10% level, *b* Indicates significance at 5% level and *c* Indicates significance at 1% level.

FIGURE 1: EU ETS Returns



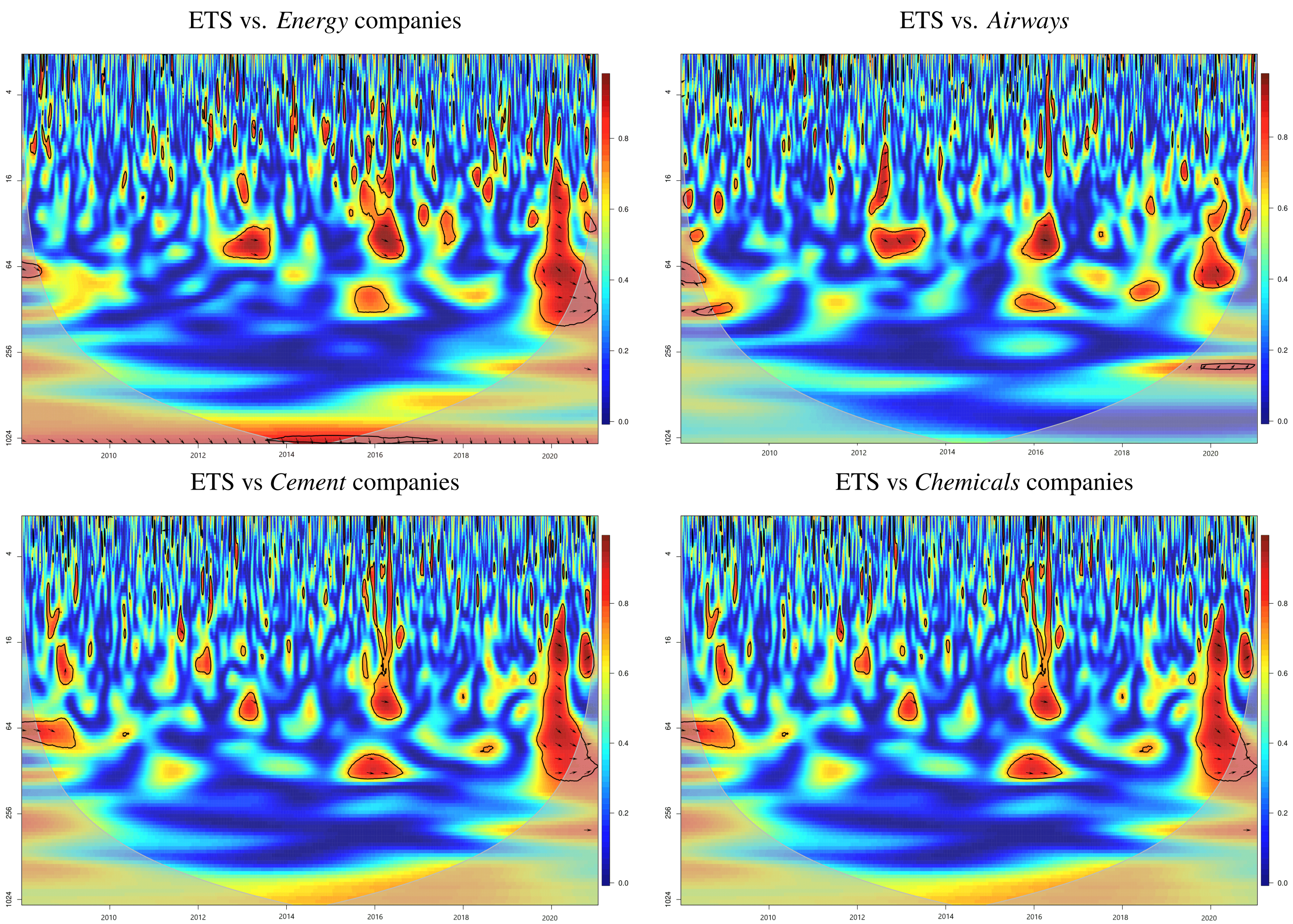
Notes: Historical Futures returns of ECX EUA Futures. Raw data on ECX EUA Historical Futures Prices are from ICE and downloaded through Nasdaq Data Link.

FIGURE 2: EU ETS Returns Volatility



Notes: Historical Volatility in the returns of ECX EUA Futures. Raw data on ECX EUA Historical Futures Prices are from ICE and downloaded through Nasdaq Data Link.

FIGURE 3: Wavelet Coherence



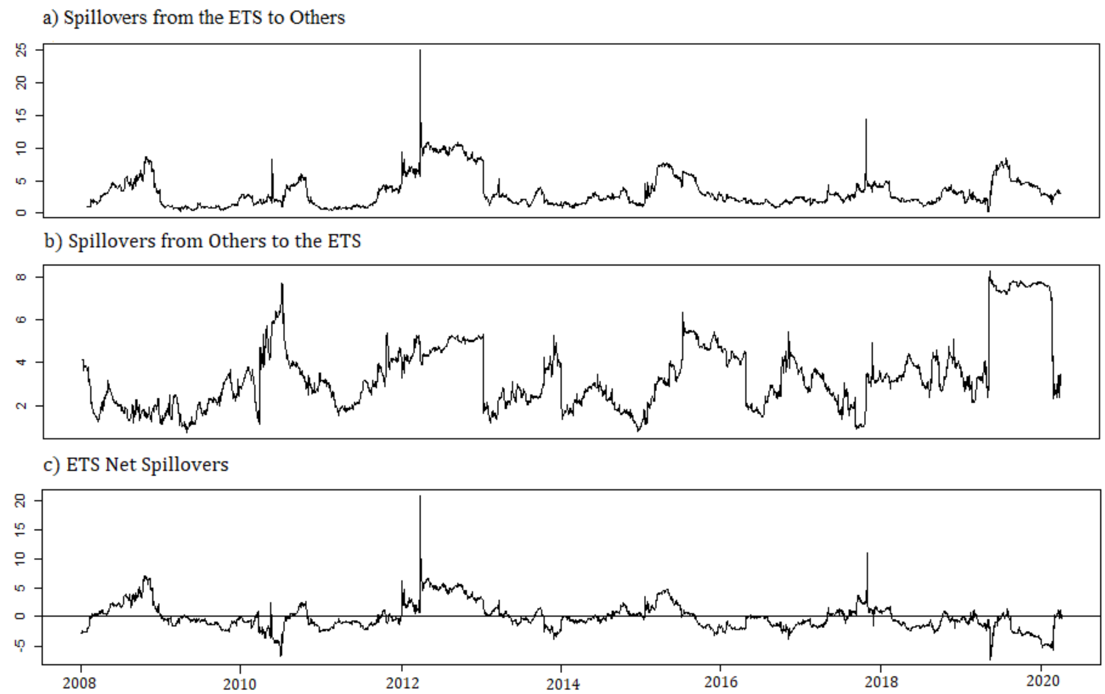
Notes: Areas of significant correlation (at the 5% significance level) are red and circled with black bands; blue areas reflect low dependence. The "cone of influence" is shown as a lighter shade. Arrows indicate whether the two series are moving in phase (→) or in anti-phase (←), and which series is leading this co-movement (when arrows point right-up or left-down, volatility in the EU ETS is leading volatility in the stock returns; vice-versa, the opposite is true).

TABLE 2: *To*, *From* and *Net* Spillovers between the EU ETS and the different sub-samples

	(1)	(2)	(3)	(4)
Panel A: EU ETS w.r.t. *Energy* companies				
To Spillovers	4.55	15.14	20.46	12.14
From Spillovers	26.60	32.20	18.39	36.41
Net Spillovers	-22.05	-17.06	2.07	-24.27
Panel B: EU ETS w.r.t *Airways*				
To Spillovers	2.80	20.62	7.75	4.46
From Spillovers	12.63	26.34	14.67	10.12
Net Spillovers	-9.83	-5.72	-6.92	-5.66
Panel C: EU ETS w.r.t *Cement* companies				
To Spillovers	2.18	9.90	3.07	2.49
From Spillovers	13.93	16.41	5.34	19.17
Net Spillovers	-11.75	-6.51	-2.27	-16.68
Panel D: EU ETS w.r.t *Chemicals* companies				
To Spillovers	4.09	5.80	4.03	11.87
From Spillovers	22.32	29.01	7.12	19.57
Net Spillovers	-18.23	-23.21	-3.09	-7.70

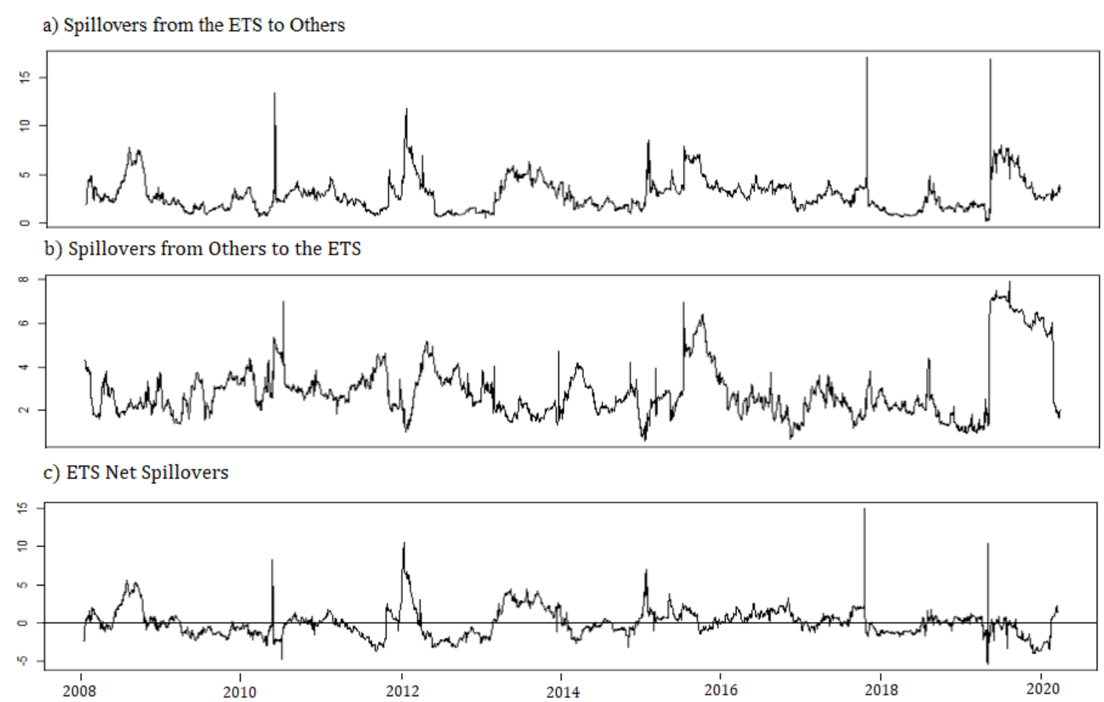
Notes: *To*, *From* and *Net* static volatility spillovers, calculated for the EU ETS with respect to firms in the four industries under analysis. Different columns refers to different time periods: col. (1) refers to the whole period under analysis (8Apr2008 -26Jan2021), col. (2) refers to the EU ETS' *Phase 2* (8Apr2008 - 31Dec2012), col. (3) refers to the EU ETS' *Phase 3* before the Covid-19 pandemic outbreak (1Jan2013 - 31Dec2019) and col. (4) refers to the ETS' *Phase 3* including the Covid-19 pandemic outbreak (1Jan2013 - 26Jan2021). The underlying variance decomposition is based on a VAR as determined by AIC information criteria and using a 70-steps-ahead forecasts of error variance decomposition. *To* spillovers indicate the gross directional spillover transmitted by the EU ETS to all other markets. *From* spillovers represent the gross directional spillovers received by the EU ETS from such markets. *Net* spillovers are the difference between spillovers transmitted and spillovers received, which are informative of whether the EU ETS is a net receiver or transmitter of volatility spillovers.

FIGURE 4: Dynamic spillovers, EU ETS w.r.t. *Energy* companies



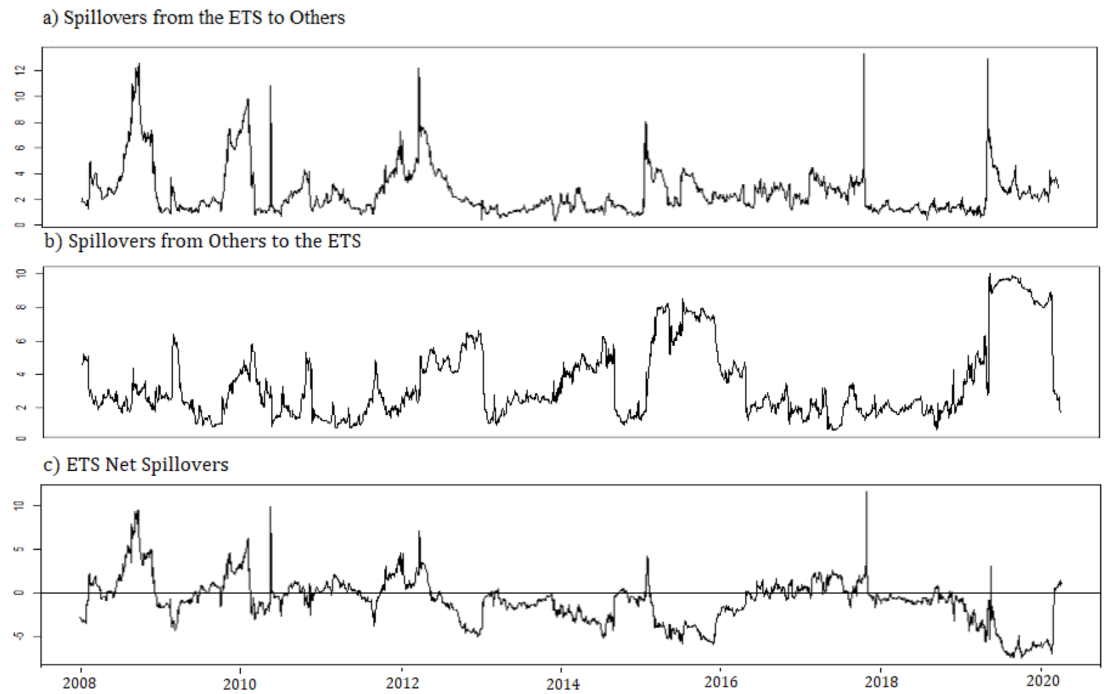
Notes: *To*, *From* and *Net* dynamic volatility spillovers calculated for the EU ETS with respect to firms in the *Energy* sub-sample. The result are obtained using the forecast error variance decomposition of 10-step-ahead forecast horizon and a 200-days rolling window.

FIGURE 5: Dynamic spillovers, EU ETS w.r.t *Airways*



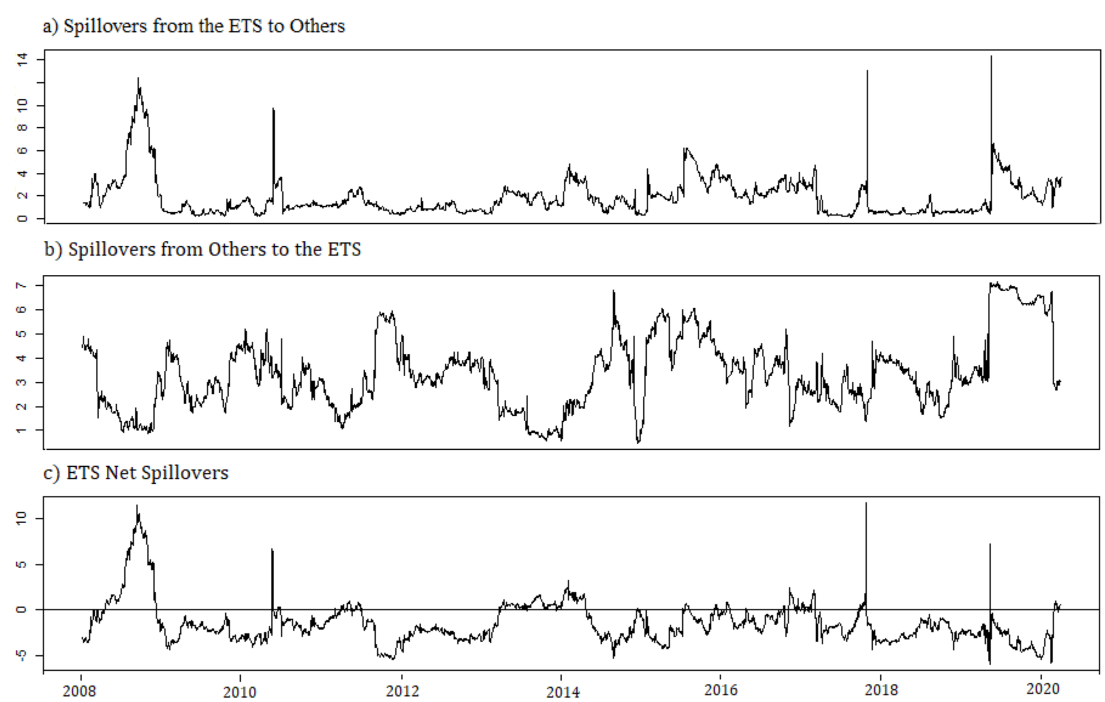
Notes: *To*, *From* and *Net* dynamic volatility spillovers calculated for the EU ETS with respect to firms in the *Airways* sub-sample. The result are obtained using the forecast error variance decomposition of 10-step-ahead forecast horizon and a 200-days rolling window.

FIGURE 6: Dynamic spillovers, EU ETS w.r.t *Cement* companies



Notes: *To*, *From* and *Net* dynamic volatility spillovers calculated for the EU ETS with respect to firms in the *Cement* sub-sample. The result are obtained using the forecast error variance decomposition of 10-step-ahead forecast horizon and a 200-days rolling window.

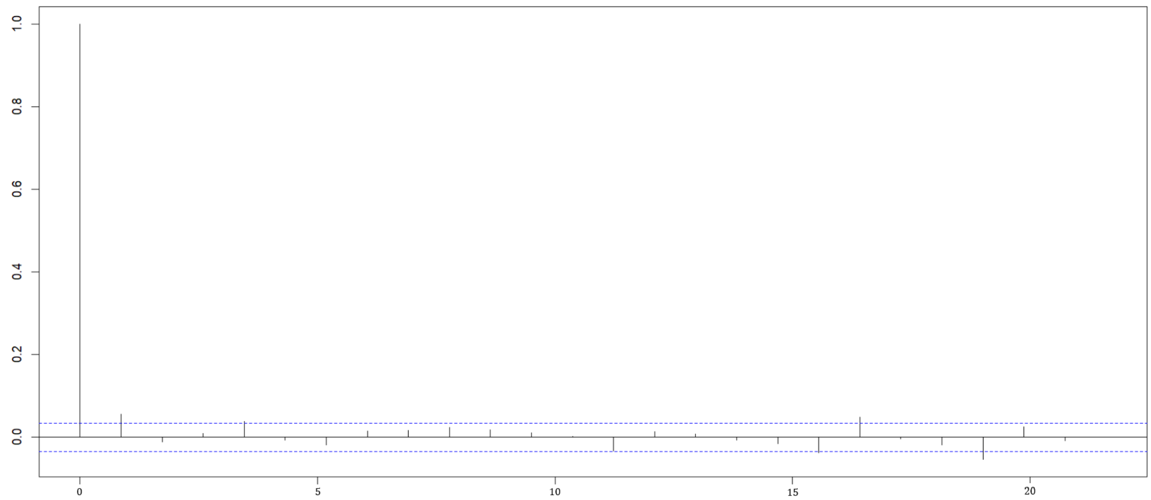
FIGURE 7: Dynamic spillovers, EU ETS w.r.t *Chemicals* companies



Notes: *To*, *From* and *Net* dynamic volatility spillovers calculated for the EU ETS with respect to firms in the *Chemicals* sub-sample. The result are obtained using the forecast error variance decomposition of 10-step-ahead forecast horizon and a 200-days rolling window.

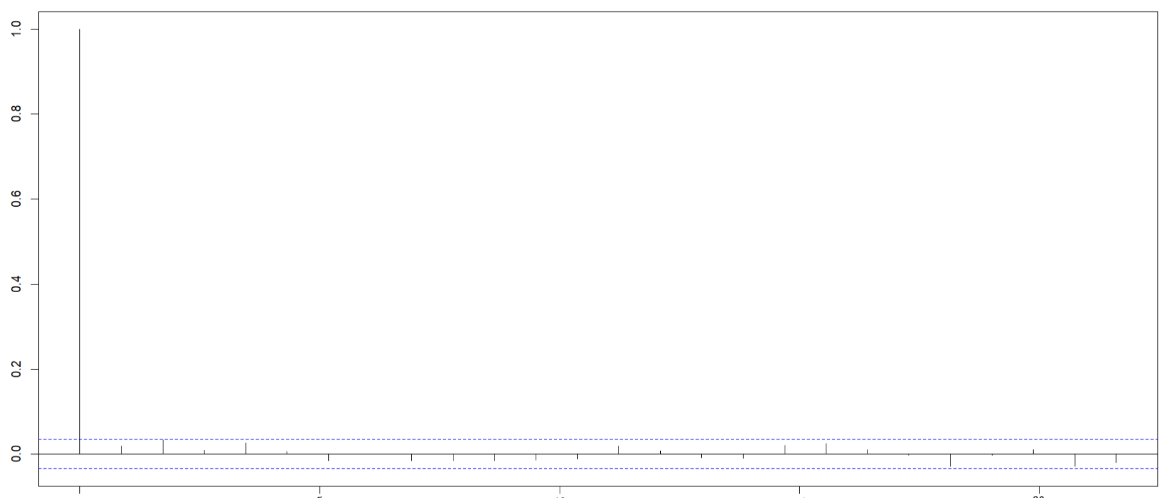
Appendix

FIGURE A.1: Autocorrelation Function - Standardized Residuals



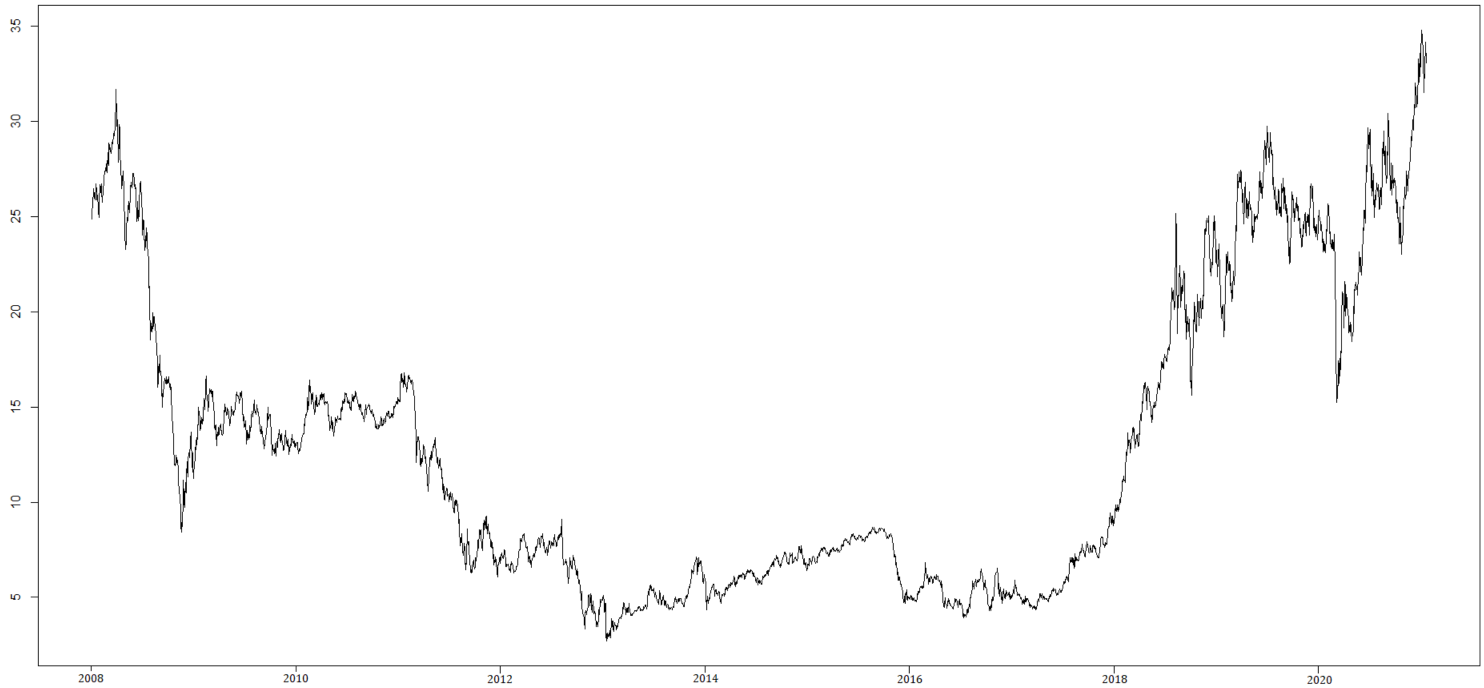
Notes: Sample Autororrelation Function for the standardised residuals of the estimation of a ARMA(0-1)eGARCH(1,1) for the EU ETS return series (see Table 5). The ACF is plotted for 25 lags. The blue dotted bands denotes the 95% confidence bounds for strict white noise.

FIGURE A.2: Autocorrelation Function - Standardized Squared Residuals



Notes: Sample Autororrelation Function for the standardised squared residuals of the estimation of a ARMA(0-1)eGARCH(1,1) for the ETS return series (see Table 5). The ACF is plotted for 25 lags. The blue dotted bands denotes the 95% confidence bounds for strict white noise.

FIGURE A.3: EU ETS Historical prices: ECX EUA Features



Notes: Historical Prices of ECX EUA Futures. Raw data are from ICE and downloaded through Nasdaq Data Link.

TABLE A.1: Static spillovers, EU ETS and *Energy* companies

Panel A: Whole period (8Apr2008 - 26Jan2021)

To / From	ETS	Edison	EDF	EnBW	Enel	E.ON	Iberdrola	RWE	SSE	Fortum	Verbund
ETS	73.41	1.69	2.56	0.25	6.43	2.26	3.41	1.88	0.79	2.66	4.67
Edison	1.25	45.09	2.38	1.46	8.01	4.86	17.83	4.91	1.40	9.71	3.11
EDF	0.42	5.91	25.19	0.14	11.03	9.08	14.01	13.69	3.09	12.50	4.94
EnBW	0.28	2.41	2.66	69.98	5.34	1.06	3.26	10.65	1.35	2.54	0.47
Enel	0.24	3.62	2.68	0.12	33.79	12.32	22.21	9.40	1.91	10.72	2.99
E.ON	0.55	4.18	3.54	0.08	12.01	32.62	14.48	16.03	1.43	12.27	2.81
Iberdrola	0.30	5.51	3.56	0.26	16.15	7.97	40.79	6.07	2.01	12.69	4.69
RWE	0.34	4.30	5.18	0.20	12.03	20.11	9.84	36.29	2.26	8.35	1.10
SSE	0.19	5.20	3.88	1.52	11.44	5.04	16.36	11.25	24.73	10.42	9.94
Fortum	0.37	5.41	3.03	0.07	9.19	8.60	17.24	8.63	2.80	33.94	10.72
Verbund	0.61	4.82	2.64	0.04	9.27	4.56	18.46	7.26	4.23	17.27	30.84
To others	4.55	43.05	32.11	4.14	100.9	75.86	137.1	89.77	21.27	99.13	45.44
From others	26.6	54.92	74.81	30.02	66.21	67.38	59.21	63.71	75.24	66.06	69.16
Net spillover	-22.05	-11.87	-42.7	-25.88	34.69	8.48	77.89	26.06	-53.97	33.07	-23.72
Total index											59.39

Panel B: EU ETS' *Phase 2* (8Apr2008 - 31Dec2012)

To / From	ETS	Edison	EDF	EnBW	Enel	E.ON	Iberdrola	RWE	SSE	Fortum	Verbund
ETS	67.81	2.45	3.18	0.15	4.86	7.33	1.76	5.22	0.18	6.84	0.59
Edison	4.08	56.31	2.01	0.20	2.09	1.28	12.35	6.55	0.51	9.27	5.36
EDF	1.85	2.35	17.43	0.89	7.11	11.02	17.75	12.04	3.02	19.69	6.85
EnBW	2.18	5.87	4.13	57.44	5.50	1.84	6.32	10.24	0.11	6.32	0.06
Enel	2.03	1.92	7.19	1.57	23.31	8.78	20.65	11.49	2.48	16.21	4.38
E.ON	0.54	3.10	7.66	0.76	9.52	19.80	15.21	16.50	4.79	16.88	5.22
Iberdrola	1.59	1.50	7.63	1.75	12.06	5.09	37.32	7.50	2.61	18.41	4.56
RWE	0.51	4.22	8.59	1.53	7.73	13.31	13.12	29.82	3.47	15.38	2.34
SSE	0.22	2.20	5.34	0.35	4.83	7.62	19.61	6.87	23.40	21.02	8.55
Fortum	1.32	2.33	5.09	0.49	3.28	5.68	18.08	6.63	5.87	37.25	13.98
Verbund	0.82	0.78	4.56	0.08	2.88	5.19	18.10	3.70	7.69	25.36	30.85
To others	15.14	26.72	55.38	7.77	59.86	67.14	142.95	86.74	30.73	155.02	51.89
From others	32.2	43.7	82.57	42.57	76.7	80.18	62.7	70.2	76.61	62.75	69.16
Net spillover	-17.06	-16.98	-27.19	-34.8	-16.84	-13.04	80.25	16.54	-45.88	92.27	-17.27
Total index											63.57

Panel C: EU ETS' *Phase 3*, before Covid-19 outbreak (1Jan2013 - 31Dec2019)

To / From	ETS	Edison	EDF	EnBW	Enel	E.ON	Iberdrola	RWE	SSE	Fortum	Verbund
ETS	81.60	1.26	0.63	0.71	0.32	1.42	1.68	0.70	1.85	1.28	8.54
Edison	9.30	46.28	5.86	1.05	8.04	8.27	13.39	3.75	0.10	1.80	2.17
EDF	0.65	4.12	47.18	0.05	4.71	15.73	5.24	7.04	1.70	9.61	3.97
EnBW	0.24	1.93	0.37	87.67	3.24	0.25	2.81	1.40	0.81	0.09	1.17
Enel	0.30	4.07	2.07	0.37	52.92	11.29	18.21	6.94	1.27	1.61	0.94
E.ON	0.64	3.22	5.88	0.09	13.05	45.84	7.93	15.31	1.82	5.04	1.18
Iberdrola	2.39	6.38	4.27	0.49	19.32	9.47	43.17	5.78	3.31	1.25	4.18
RWE	0.31	2.24	6.55	0.17	11.34	30.42	5.75	35.83	1.79	4.11	1.49
SSE	1.15	0.54	1.21	0.30	4.86	7.61	8.75	6.35	54.49	3.54	11.20
Fortum	1.71	1.13	4.61	0.07	7.72	13.99	5.09	6.28	2.68	46.25	10.47
Verbund	3.77	1.48	1.00	0.26	1.94	3.74	4.29	5.17	1.25	9.71	67.38
To others	20.46	26.37	32.45	3.56	74.54	102.19	73.14	58.72	16.58	38.04	45.31
From others	18.39	53.73	52.82	12.31	47.07	54.16	56.84	64.17	45.51	53.75	32.61
Net spillover	2.07	-27.36	-20.37	-8.75	27.47	48.03	16.3	-5.45	-28.93	-15.71	12.7
Total index											44.67

Panel D: EU ETS' *Phase 3*, including Covid-19 outbreak (1Jan2013 - 26Jan2021)

To / From	ETS	Edison	EDF	EnBW	Enel	E.ON	Iberdrola	RWE	SSE	Fortum	Verbund
ETS	63.59	4.04	2.66	2.12	3.23	2.77	4.95	1.40	1.53	4.28	9.43
Edison	1.04	43.29	3.33	1.80	11.17	8.59	15.88	4.15	0.87	6.79	3.10
EDF	0.69	9.17	26.04	0.01	10.24	11.42	13.38	8.32	2.57	12.36	5.80
EnBW	0.28	3.23	2.06	67.10	3.58	1.20	5.20	7.13	2.04	4.69	3.47
Enel	0.91	8.42	4.28	0.19	36.14	11.16	18.26	7.41	2.71	7.66	2.86
E.ON	2.10	7.18	3.07	0.19	9.84	44.06	9.06	14.02	0.88	7.87	1.74
Iberdrola	0.36	11.89	3.57	0.31	18.45	9.63	32.88	6.93	3.32	6.79	5.87
RWE	3.39	7.48	3.75	0.10	10.09	26.48	9.06	29.47	1.11	6.83	2.24
SSE	1.90	10.24	3.01	1.47	10.77	6.09	16.97	7.45	20.39	9.61	12.10
Fortum	0.79	7.45	3.44	0.06	9.89	11.74	12.10	7.54	2.44	34.54	10.00
Verbund	0.68	10.27	3.07	0.03	8.67	4.91	15.76	7.44	2.72	14.72	31.73
To others	12.14	79.37	32.24	6.28	95.93	93.99	120.62	71.79	20.19	81.6	56.61
From others	36.41	56.72	73.96	32.88	63.86	55.95	67.12	70.53	79.61	65.45	68.27
Net spillover	-24.27	22.65	-41.72	-26.6	32.07	38.04	53.5	1.26	-59.42	16.15	-11.66
Total index											60.98

Notes: *To*, *From* and *Net* static volatility spillovers, calculated for the EU ETS with respect to firms in the *Energy* industry. Different columns refers to different time periods. The underlying variance decomposition is based on a VAR as determined by AIC information criteria and using a 70-steps-ahead forecasts of error variance decomposition. Each entry represents the estimated contribution *to* the asset on the row coming *from* innovations affecting the asset on the column. Elements on the main diagonal represent the own-variable spillovers imputable to self-caused variations within a given market. The off-diagonal column sums are the directional volatility spillovers contributions going from each asset on the column *to* others; the off-diagonal row sums are the directional volatility spillovers contributions "received" by each asset on the column *from* others. The difference between *from* and *to* spillovers are the *net* returns spillovers, indicating whether a given asset is a net transmitter or receiver of shocks. The total spillover index reflects the overall percentage of the volatility forecast error variance deriving from other assets.

TABLE A.2: Static spillovers, EU ETS and *Airways*

Panel A: Whole period (8Apr2008 - 26Jan2021)										
To / From	ETS	AF-KLM	easyJet	Finnair	Ryanair	Luft	Norw	SAS	Turkish	Aeroflot
ETS	87.37	1.85	0.26	0.07	0.44	4.56	2.13	1.73	1.32	0.27
AF-KLM	0.39	44.86	5.50	1.90	8.29	21.08	7.23	6.24	1.49	3.02
easyJet	0.59	9.80	33.88	1.08	17.87	16.74	10.79	2.02	5.02	2.21
Finnair	0.09	7.67	6.42	54.49	4.33	9.12	10.10	4.01	1.17	2.61
Ryanair	0.14	4.58	21.27	1.39	49.73	9.30	6.55	1.05	5.05	0.93
Luft	0.54	17.66	12.33	2.47	8.86	35.86	10.71	3.80	4.16	3.60
Norw	0.20	7.50	9.83	1.68	5.64	8.00	62.15	3.10	0.83	1.07
SAS	0.47	6.34	2.01	0.74	7.79	10.41	1.85	68.08	1.14	1.18
Turkish	0.15	3.05	2.74	0.54	8.02	5.59	2.70	0.85	73.34	3.02
Aeroflot	0.23	3.60	3.44	0.07	2.91	4.68	1.73	1.41	3.27	78.66
To others	2.8	62.05	63.80	9.94	64.15	89.48	53.79	24.21	23.45	17.91
From others	12.63	55.14	66.12	45.52	50.26	64.13	37.85	31.93	26.66	21.34
Net spillover	-9.83	6.91	-2.32	-35.58	13.89	25.35	15.94	-7.72	-3.21	-3.43
Total index										41.16

Panel B: EU ETS' *Phase 2* (8Apr2008 - 31Dec2012)

To / From	ETS	AF-KLM	easyJet	Finnair	Ryanair	Luft	Norw	SAS	Turkish	Aeroflot
ETS	73.66	3.95	0.09	2.02	0.08	10.46	2.13	1.43	5.46	0.72
AF-KLM	4.79	43.88	4.26	3.44	6.52	21.36	5.15	3.19	4.09	3.32
easyJet	0.03	6.00	51.98	1.20	19.44	7.34	1.88	1.37	10.61	0.14
Finnair	3.40	4.82	4.77	61.19	9.77	2.78	5.13	1.15	3.85	3.13
Ryanair	0.28	1.42	24.95	0.85	55.82	2.08	4.19	0.87	8.93	0.61
Luft	1.64	19.23	10.04	4.59	6.38	35.35	6.55	2.82	10.33	3.07
Norw	1.32	8.29	7.24	0.86	15.66	9.03	52.13	0.27	3.37	1.82
SAS	8.58	6.32	2.81	7.20	6.53	6.61	4.47	45.62	7.87	4.01
Turkish	0.48	7.12	7.69	0.83	11.18	7.61	3.98	1.75	57.18	2.18
Aeroflot	0.10	2.47	10.10	0.61	5.36	3.85	3.31	0.50	1.43	72.26
To others	20.62	59.62	71.95	21.6	80.92	71.12	36.79	13.35	55.94	19.00
From others	26.34	56.12	48.01	38.8	44.18	64.65	47.86	54.4	42.82	27.73
Net spillover	-5.72	3.50	23.94	-17.2	36.74	6.47	-11.07	-41.05	13.12	-8.73
Total index										45.09

Panel C: EU ETS' *Phase 3*, before Covid-19 outbreak (1Jan2013 - 31Dec2019)

To / From	ETS	AF-KLM	easyJet	Finnair	Ryanair	Luft	Norw	SAS	Turkish	Aeroflot
ETS	85.33	0.15	1.68	0.31	1.03	0.71	0.03	9.86	0.32	0.58
AF-KLM	0.65	65.35	2.82	2.56	2.88	17.44	4.55	0.94	0.18	2.61
easyJet	2.05	8.04	49.59	1.02	18.66	15.62	2.93	1.53	0.16	0.38
Finnair	0.28	0.65	0.83	85.58	0.77	3.05	6.47	0.98	1.22	0.17
Ryanair	0.21	2.23	19.27	2.96	54.81	14.91	4.25	0.93	0.29	0.14
Luft	2.78	12.46	12.95	3.32	6.99	56.60	2.87	0.37	0.73	0.93
Norw	0.10	1.92	5.98	1.15	9.27	2.38	78.29	0.25	0.12	0.55
SAS	0.12	0.66	0.54	0.98	0.41	0.62	0.23	95.96	0.20	0.28
Turkish	0.08	0.48	0.67	1.06	2.22	1.84	1.60	0.15	90.69	1.21
Aeroflot	1.48	0.20	0.69	0.77	1.52	0.54	4.23	0.13	0.94	89.51
To others	7.75	26.79	45.43	14.13	43.75	57.11	27.16	15.14	4.16	6.85
From others	14.67	34.63	50.39	14.42	45.19	43.4	21.72	4.04	9.31	10.5
Net spillover	-6.92	-7.84	-4.96	-0.29	-1.44	13.71	5.44	11.10	-5.15	-3.65
Total index										24.83

Panel D: EU ETS' *Phase 3*, including Covid-19 outbreak (1Jan2013 - 26Jan2021)

To / From	ETS	AF-KLM	easyJet	Finnair	Ryanair	Luft	Norw	SAS	Turkish	Aeroflot
ETS	89.88	1.14	0.74	0.05	0.65	3.32	2.00	1.84	0.18	0.20
AF-KLM	0.48	44.12	5.95	2.12	5.89	20.66	11.61	5.24	0.80	3.13
easyJet	0.63	14.14	24.80	0.58	14.77	24.12	13.39	2.91	2.46	2.20
Finnair	0.21	11.96	5.43	48.69	3.42	14.90	7.74	5.91	0.45	1.29
Ryanair	0.25	7.72	17.94	1.60	38.12	19.18	11.02	0.74	2.74	0.69
Luft	0.37	17.65	12.37	2.05	9.20	36.76	12.58	3.64	2.12	3.28
Norw	0.57	10.93	9.38	0.63	7.38	11.42	52.38	5.80	0.78	0.73
SAS	0.08	4.31	1.14	0.17	2.77	12.28	2.06	76.63	0.10	0.46
Turkish	0.70	1.60	1.86	0.54	2.96	5.04	4.91	0.40	80.15	1.83
Aeroflot	1.17	4.74	1.47	0.13	1.14	6.46	1.61	2.39	3.23	77.66
To others	4.46	74.19	56.28	7.87	48.18	117.38	66.92	28.87	12.86	13.81
From others	10.12	55.88	75.20	51.31	61.88	63.26	47.62	23.37	19.84	22.34
Net spillover	-5.66	18.31	-18.92	-43.44	-13.7	54.12	19.30	5.50	-6.98	-8.53
Total index										43.08

Notes: *To*, *From* and *Net* static volatility spillovers, calculated for the EU ETS with respect to firms in the *Airways* industry. Different columns refers to different time periods. The underlying variance decomposition is based on a VAR as determined by AIC information criteria and using a 70-steps-ahead forecasts of error variance decomposition. Each entry represents the estimated contribution *to* the asset on the row coming *from* innovations affecting the asset on the column. Elements on the main diagonal represent the own-variable spillovers imputable to self-caused variations within a given market. The off-diagonal column sums are the directional volatility spillovers contributions going from each asset on the column *to* others; the off-diagonal row sums are the directional volatility spillovers contributions "received" by each asset on the column *from* others. The difference between *from* and *to* spillovers are the *net* returns spillovers, indicating whether a given asset is a net transmitter or receiver of shocks. The total spillover index reflects the overall percentage of the volatility forecast error variance deriving from other assets.

TABLE A.3: Static spillovers, EU ETS and *Cement* companies

Panel A: Whole period (8Apr2008 - 26Jan2021))

To / From	ETS	Buzzi Unicem	Heidelberg	LafargeHolcim	CRH	Vicat	OYAK	Cementir
ETS	86.08	3.44	2.91	2.51	1.73	2.06	0.03	1.25
Buzzi Unicem	0.34	36.65	9.75	12.85	18.67	8.95	0.12	12.67
Heidelberg	0.16	18.30	30.62	15.81	13.92	13.62	0.14	7.44
LafargeHolcim	0.23	18.71	9.02	31.88	14.29	15.61	0.09	10.17
CRH	0.47	16.84	11.85	13.83	36.44	10.62	0.05	9.91
Vicat	0.14	15.23	6.82	13.00	16.73	37.58	0.15	10.35
OYAK	0.16	6.02	0.54	2.49	2.83	19.35	66.17	2.44
Cementir	0.68	14.22	6.42	11.28	11.78	7.64	0.33	47.65
To others	2.18	92.76	47.31	71.77	79.95	77.85	0.91	54.23
From others	13.93	63.35	69.39	68.12	63.57	62.42	33.83	52.35
Net spillover	-11.75	29.41	-22.08	3.65	16.38	15.43	-32.92	1.88
Total index								53.37

Panel B: EU ETS' *Phase 2* (8Apr2008 - 31Dec2012)

To / From	ETS	Buzzi Unicem	Heidelberg	LafargeHolcim	CRH	Vicat	OYAK	Cementir
ETS	83.59	6.82	1.11	3.57	3.23	1.14	0.09	0.45
Buzzi Unicem	1.66	44.08	3.86	14.90	19.02	5.98	1.56	8.93
Heidelberg	2.72	19.52	23.97	19.94	11.51	12.70	4.74	4.91
LafargeHolcim	2.33	18.89	2.61	35.17	15.30	15.11	4.58	6.00
CRH	0.67	14.00	2.97	20.61	44.63	7.07	3.94	6.11
Vicat	1.60	12.24	1.47	18.12	20.78	32.57	3.81	9.42
OYAK	0.30	8.23	0.53	12.09	8.24	19.57	43.11	7.94
Cementir	0.62	12.96	4.15	13.46	13.89	4.64	3.18	47.09
To others	9.90	92.66	16.70	102.69	91.97	66.21	21.9	43.76
From others	16.41	55.91	76.04	64.82	55.37	67.44	56.9	52.9
Net spillover	-6.51	36.75	-59.34	37.87	36.60	-1.23	-35.00	-9.14
Total index								55.72

Panel C: EU ETS' *Phase 3*, before Covid-19 outbreak (1Jan2013 - 31Dec2019)

To / From	ETS	Buzzi Unicem	Heidelberg	LafargeHolcim	CRH	Vicat	OYAK	Cementir
ETS	94.67	0.46	3.77	0.09	0.42	0.32	0.21	0.07
Buzzi Unicem	0.52	37.26	17.64	12.97	12.96	6.98	0.35	11.32
Heidelberg	0.31	15.01	37.25	14.63	13.70	10.84	0.58	7.67
LafargeHolcim	0.17	11.91	16.10	37.76	13.25	13.61	0.18	7.02
CRH	0.40	14.98	18.92	13.68	33.25	11.26	0.23	7.29
Vicat	0.43	8.45	13.68	13.22	9.57	48.00	0.22	6.43
OYAK	0.20	2.61	0.96	0.27	1.44	7.23	86.89	0.42
Cementir	1.04	12.72	9.14	9.06	8.82	7.59	1.03	50.60
To others	3.07	66.14	80.21	63.92	60.16	57.83	2.80	40.22
From others	5.34	62.74	62.74	62.24	66.76	52.00	13.13	49.40
Net spillover	-2.27	3.40	17.47	1.68	-6.60	5.83	-10.33	-9.18
Total index								46.79

Panel D: EU ETS' *Phase 3*, including Covid-19 outbreak (1Jan2013 - 26Jan2021)

To / From	ETS	Buzzi Unicem	Heidelberg	LafargeHolcim	CRH	Vicat	OYAK	Cementir
ETS	80.84	2.60	7.13	2.47	2.99	2.30	0.05	1.63
Buzzi Unicem	0.15	33.18	15.90	12.34	13.14	11.32	0.51	13.46
Heidelberg	0.30	17.94	27.32	12.25	15.18	17.66	0.19	9.16
LafargeHolcim	0.27	17.67	12.84	29.05	12.37	15.05	0.77	11.99
CRH	0.39	17.85	17.27	12.61	24.66	15.99	0.69	10.54
Vicat	0.46	14.53	16.08	11.01	11.64	38.38	0.53	7.38
OYAK	0.40	5.58	6.52	1.09	2.16	12.17	71.69	0.41
Cementir	0.52	14.21	8.59	9.70	8.78	9.84	0.75	47.62
To others	2.49	90.38	84.33	61.47	66.26	84.33	3.49	54.57
From others	19.17	66.82	72.68	70.96	75.34	61.63	28.33	52.39
Net spillover	-16.68	23.56	11.65	-9.49	-9.08	22.7	-24.84	2.18
Total index								55.91

Notes: *To*, *From* and *Net* static volatility spillovers, calculated for the eu ETS with respect to firms in the *Cement* industry. Different columns refers to different time periods. The underlying variance decomposition is based on a VAR as determined by AIC information criteria and using a 70-steps-ahead forecasts of error variance decomposition. Each entry represents the estimated contribution *to* the asset on the row coming *from* innovations affecting the asset on the column. Elements on the main diagonal represent the own-variable spillovers imputable to self-caused variations within a given market. The off-diagonal column sums are the directional volatility spillovers contributions going from each asset on the column *to* others; the off-diagonal row sums are the directional volatility spillovers contributions "received" by each asset on the column *from* others. The difference between *from* and *to* spillovers are the *net* returns spillovers, indicating whether a given asset is a net transmitter or receiver of shocks. The total spillover index reflects the overall percentage of the volatility forecast error variance deriving from other assets.

TABLE A.4: Static spillovers, EU ETS and *Chemicals* companies

Panel A: Whole period (8Apr2008 - 26Jan2021)

To / From	ETS	BASF	Bayer	Solvay	DSM	AirLiq	Umicore	Arkema	Lanxess	Linde	Yara	AkzNob
ETS	77.69	1.12	3.02	3.09	1.35	3.26	0.51	0.44	2.61	3.75	1.01	2.16
BASF	0.31	20.29	10.80	8.52	8.97	10.31	5.99	2.46	9.16	7.67	9.50	6.02
Bayer	0.36	14.37	27.99	8.24	8.11	9.99	4.99	1.94	7.03	6.24	6.72	4.02
Solvay	0.10	12.33	9.64	20.44	9.84	8.96	6.24	3.71	9.52	6.75	5.16	7.31
DSM	0.39	9.48	7.76	7.00	24.00	9.74	5.71	2.94	7.58	7.23	10.85	7.31
Air Liquide	0.73	13.27	8.10	7.55	8.71	22.47	5.58	2.64	6.91	7.74	9.64	6.67
Umicore	0.25	9.74	7.44	6.59	8.48	7.56	23.00	1.59	9.29	8.01	13.74	4.33
Arkema	0.17	12.76	7.26	8.50	8.66	9.60	5.41	15.24	9.12	5.59	9.99	7.70
Lanxess	0.29	12.88	8.80	8.63	9.26	10.15	7.28	3.18	17.09	6.55	9.77	6.12
Linde	0.42	9.50	7.77	4.67	10.06	9.22	8.88	0.85	6.04	26.40	11.82	4.37
Yara	0.65	6.71	6.19	4.35	9.38	8.02	7.27	1.67	8.06	6.01	35.03	6.66
AkzoNobel	0.42	10.97	7.97	7.71	10.15	10.48	4.43	2.63	8.53	6.63	10.81	19.27
To others	4.09	113.13	84.75	74.85	92.97	97.29	62.29	24.05	83.85	72.17	99.01	62.67
From others	22.32	79.71	72.01	79.56	75.99	77.54	77.02	84.76	82.91	73.60	64.97	80.73
Net spillover	-18.23	33.42	12.74	-4.71	16.98	19.75	-14.73	-60.71	0.94	-1.43	34.04	-18.06
Total index												72.59

Panel B: EU ETS' *Phase 2* (8Apr2008 - 31Dec2012)

To / From	ETS	BASF	Bayer	Solvay	DSM	AirLiq	Umicore	Arkema	Lanxess	Linde	Yara	AkzNob
ETS	71.00	2.22	0.96	6.11	0.77	0.96	0.21	3.77	2.49	0.88	5.68	4.96
BASF	0.28	16.37	10.02	6.17	10.99	7.69	3.44	3.20	15.87	3.39	18.46	4.11
Bayer	0.68	12.62	19.56	5.89	10.32	7.64	1.47	2.94	14.55	2.77	16.62	4.94
Solvay	1.79	7.38	7.12	23.39	12.91	2.63	1.93	5.29	16.69	4.12	9.27	7.49
DSM	0.48	8.16	7.46	6.49	19.09	6.27	3.12	3.71	15.52	5.32	18.20	6.16
Air Liquide	0.31	12.48	7.49	4.86	9.44	17.34	6.37	3.20	13.00	3.70	16.35	5.46
Umicore	0.21	6.40	4.35	5.43	11.54	6.09	12.57	2.33	16.54	4.16	23.78	6.59
Arkema	0.08	10.22	6.63	9.36	10.09	5.08	4.12	10.44	16.86	3.39	16.60	7.14
Lanxess	0.06	10.48	7.95	6.33	11.30	6.66	4.07	3.94	25.37	2.87	15.85	5.10
Linde	0.12	5.38	4.67	3.46	11.34	5.75	6.89	0.82	13.69	15.71	26.73	5.43
Yara	0.27	3.46	5.11	2.72	9.71	4.16	5.48	1.78	12.09	2.44	45.82	6.95
AkzoNobel	1.52	7.40	5.85	6.15	9.95	6.18	2.00	3.66	13.52	5.38	19.26	19.15
To others	5.80	86.20	67.61	62.97	108.36	59.11	39.1	34.64	150.82	38.42	186.80	64.33
From others	29.01	83.62	80.44	76.62	80.89	82.66	87.42	89.57	74.61	84.28	54.17	80.87
Net spillover	-23.21	2.58	-12.83	-13.65	27.47	-23.55	-48.32	-54.93	76.21	-45.86	132.63	-16.54
Total index												75.35

Panel C: EU ETS' *Phase 3*, before Covid-19 outbreak (1Jan2013 - 31Dec2019)

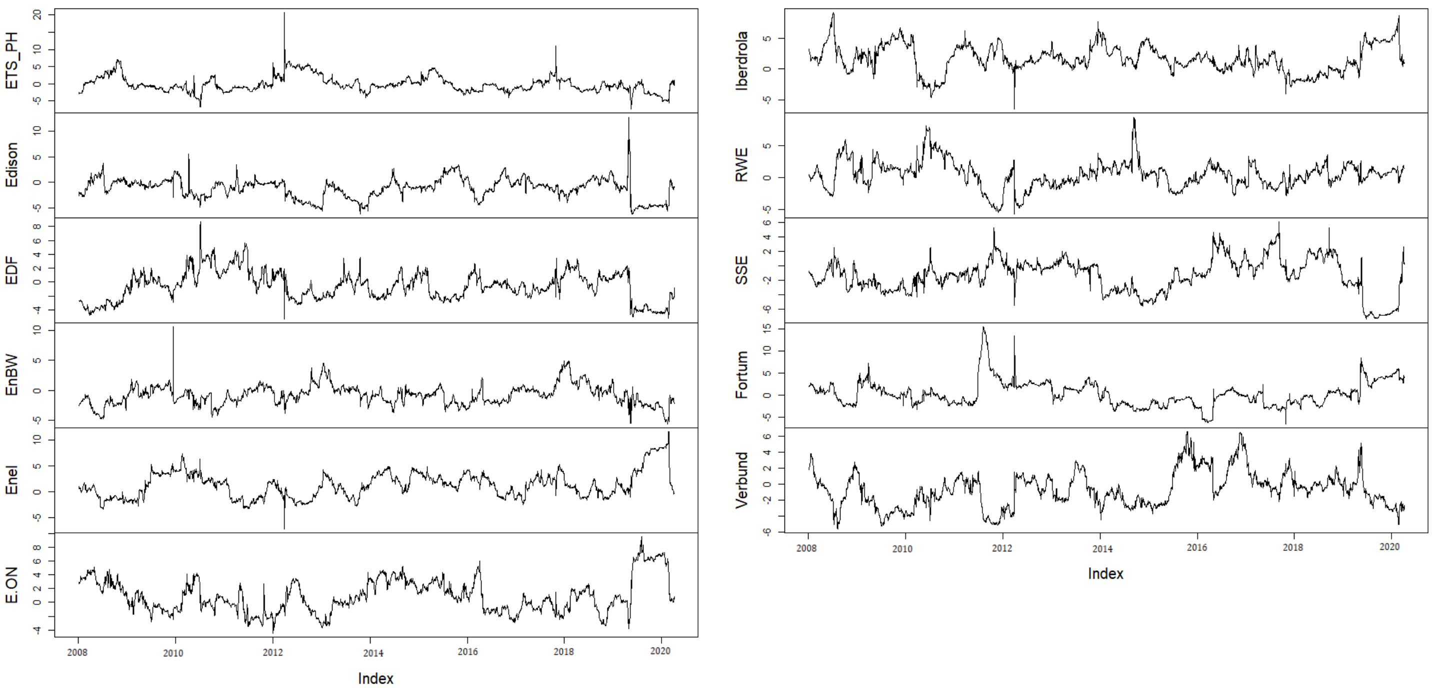
To / From	ETS	BASF	Bayer	Solvay	DSM	AirLiq	Umicore	Arkema	Lanxess	Linde	Yara	AkzNob
ETS	92.89	1.07	0.17	1.52	0.05	0.20	0.26	0.04	1.22	0.05	2.22	0.32
BASF	0.05	31.21	8.61	10.71	4.59	11.73	6.71	2.73	6.28	5.01	3.29	9.08
Bayer	0.47	16.51	36.54	8.36	4.10	12.18	5.18	1.40	4.56	5.50	2.52	2.66
Solvay	0.09	16.30	6.58	22.00	6.38	11.55	9.14	3.16	6.84	5.64	4.99	7.33
DSM	0.28	11.46	4.50	9.89	29.53	14.58	4.58	1.93	4.54	7.40	2.03	9.26
Air Liquide	0.65	16.29	6.26	9.70	6.05	32.65	2.02	1.62	3.83	6.59	7.22	7.11
Umicore	0.18	9.55	3.96	7.75	1.72	4.95	57.65	0.75	3.00	8.28	1.01	1.21
Arkema	0.09	19.34	5.30	10.39	3.63	9.72	3.01	32.56	4.45	2.57	1.62	7.33
Lanxess	0.26	16.36	6.05	14.90	5.79	9.23	8.07	3.05	19.83	6.98	3.47	6.00
Linde	0.74	12.13	4.70	5.87	7.30	12.46	7.18	0.41	5.52	39.66	1.20	2.83
Yara	0.63	12.95	4.42	12.44	4.43	12.82	4.36	0.84	5.76	8.15	25.78	7.42
AkzoNobel	0.59	15.02	7.68	11.53	6.43	11.33	1.53	1.31	6.14	2.86	3.59	31.97
To others	4.03	146.98	58.23	103.06	50.47	110.75	52.04	17.24	52.14	59.03	33.16	60.55
From others	7.12	68.79	63.44	78.00	70.45	67.34	42.36	67.45	80.16	60.34	74.22	68.01
Net spillover	-3.09	78.19	-5.21	25.06	-19.98	43.41	9.68	-50.21	-28.02	-1.31	-41.06	-7.46
Total index												62.31

Panel D: EU ETS' *Phase 3*, including Covid-19 outbreak (1Jan2013 - 26Jan2021)

To / From	ETS	BASF	Bayer	Solvay	DSM	AirLiq	Umicore	Arkema	Lanxess	Linde	Yara	AkzNob
ETS	80.42	0.52	2.21	2.54	0.50	4.10	0.12	0.17	3.60	3.79	0.46	1.56
BASF	0.59	22.26	9.26	10.46	5.19	12.07	8.14	2.24	4.84	13.66	2.88	8.42
Bayer	1.34	13.70	31.77	8.87	3.99	11.29	7.53	1.49	3.85	10.00	2.74	3.43
Solvay	0.45	14.55	7.98	16.36	6.59	12.28	9.75	2.55	5.05	13.21	4.23	6.99
DSM	1.81	8.61	5.81	9.04	29.55	14.56	6.43	2.07	2.82	9.48	1.83	7.99
Air Liquide	2.06	13.04	7.21	8.96	7.09	26.62	4.34	1.88	3.26	12.88	4.86	7.79
Umicore	0.73	11.06	6.54	8.41	3.09	7.22	39.35	0.90	2.74	16.06	1.61	2.30
Arkema	0.39	15.36	7.04	8.58	5.74	13.04	4.52	20.47	4.16	10.46	2.20	8.04
Lanxess	0.64	14.10	8.31	10.46	6.35	12.30	8.61	2.24	11.41	15.38	3.40	6.80
Linde	1.76	10.36	6.66	6.71	6.64	12.45	10.09	0.82	3.52	33.78	1.45	5.77
Yara	1.72	11.54	6.22	9.61	6.49	14.42	5.56	1.01	4.23	15.38	16.07	7.73
AkzoNobel	0.38	13.04	8.41	8.98	7.57	14.11	4.63	1.45	4.88	10.28	3.44	22.85
To others	11.87	125.88	75.65	92.62	59.24	127.84	69.72	16.82	42.95	130.58	29.1	66.82
From others	19.57	77.75	68.23	83.63	70.45	73.37	60.66	79.53	88.59	66.23	83.91	77.17
Net spillover	-7.7	48.13	7.42	8.99	-11.21	54.47	9.06	-62.71	-45.64	64.35	-54.81	-10.35
Total index												70.76

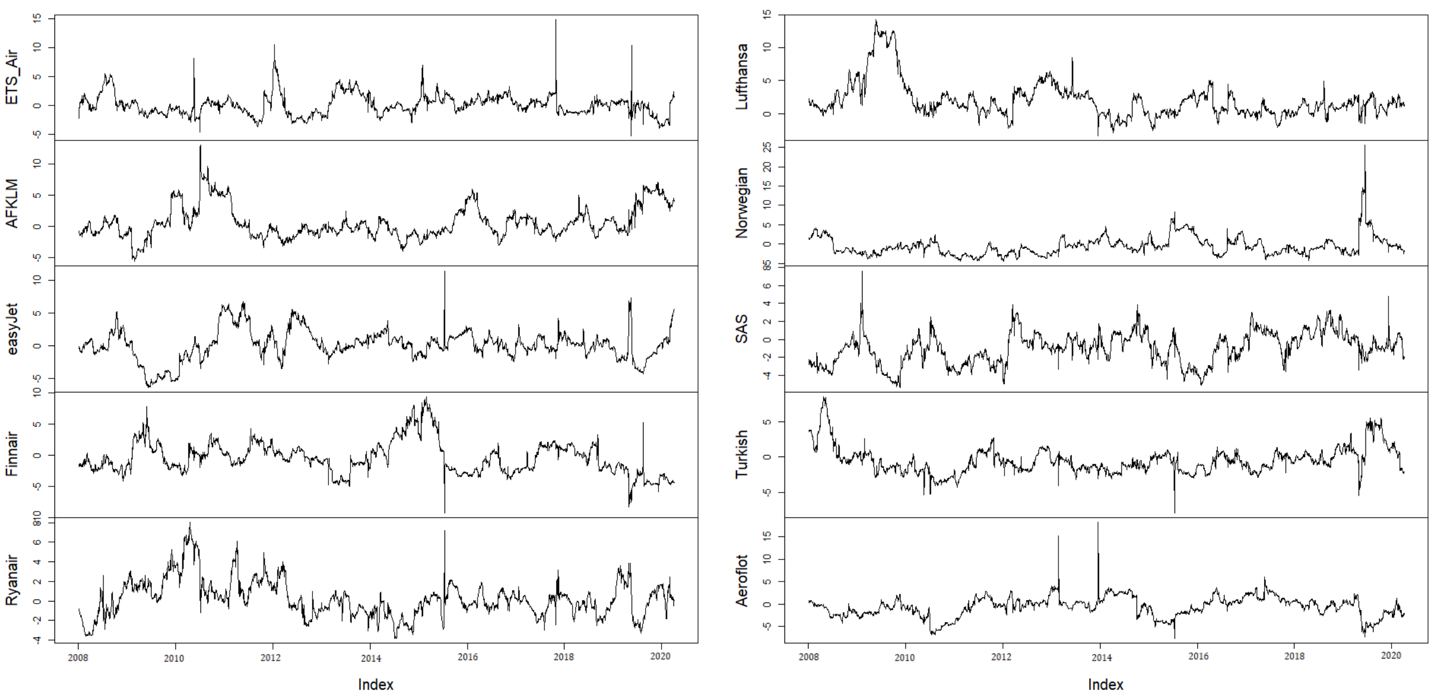
Notes: *To*, *From* and *Net* static volatility spillovers, calculated for the EU ETS with respect to firms in the *Chemicals* industry. Different columns refers to different time periods. The underlying variance decomposition is based on a VAR as determined by AIC information criteria and using a 70-steps-ahead forecasts of error variance decomposition. Each entry represents the estimated contribution *to* the asset on the row coming *from* innovations affecting the asset on the column. Elements on the main diagonal represent the own-variable spillovers imputable to self-caused variations within a given market. The off-diagonal column sums are the directional volatility spillovers contributions going from each asset on the column *to* others; the off-diagonal row sums are the directional volatility spillovers contributions "received" by each asset on the column *from* others. The difference between *from* and *to* spillovers are the *net* returns spillovers, indicating whether a given asset is a net transmitter or receiver of shocks. The total spillover index reflects the overall percentage of the volatility forecast error variance deriving from other assets.

FIGURE A.4: Dynamic spillovers, EU ETS and *Energy* companies



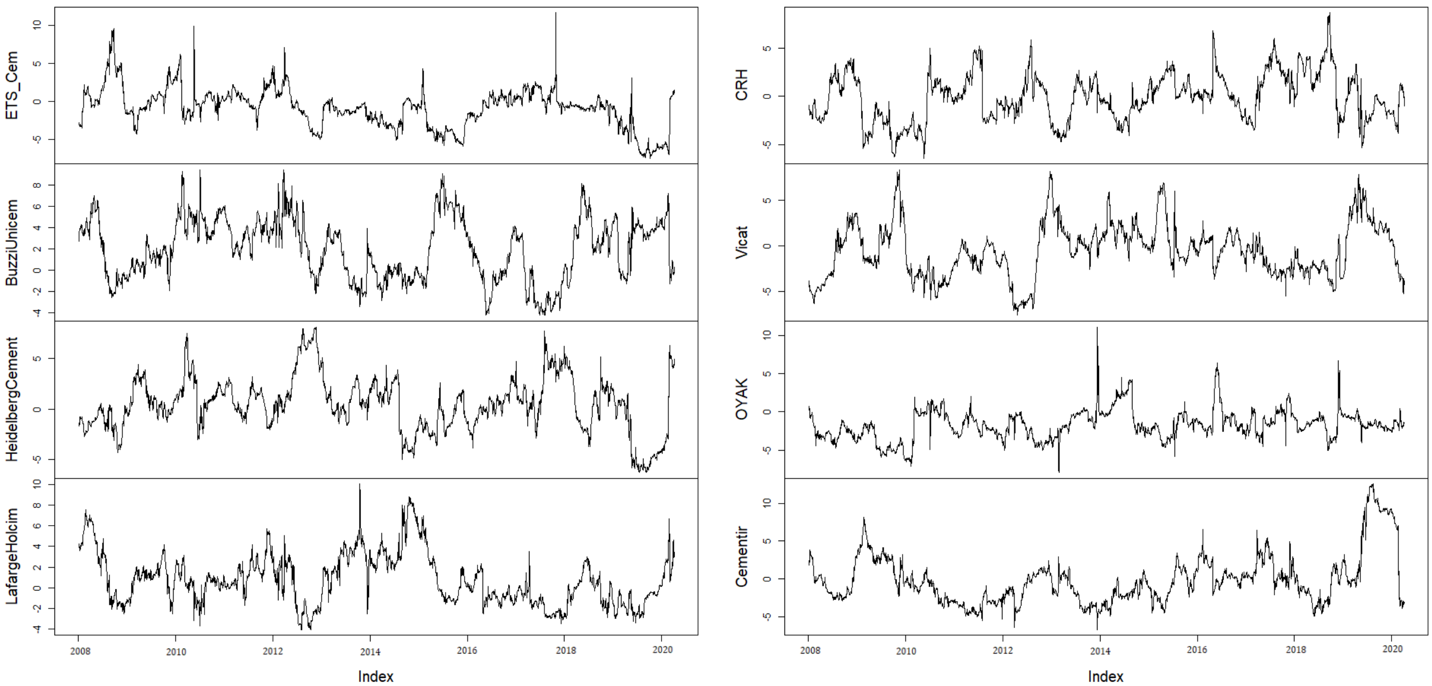
Notes: *Net* volatility spillovers calculated for the ETS and firms in the *Energy* sub-sample. The result are obtained using the forecast error variance decomposition of 10-step-ahead forecast horizon and a 200-days rolling window.

FIGURE A.5: Dynamic spillovers, EU ETS and *Airways*



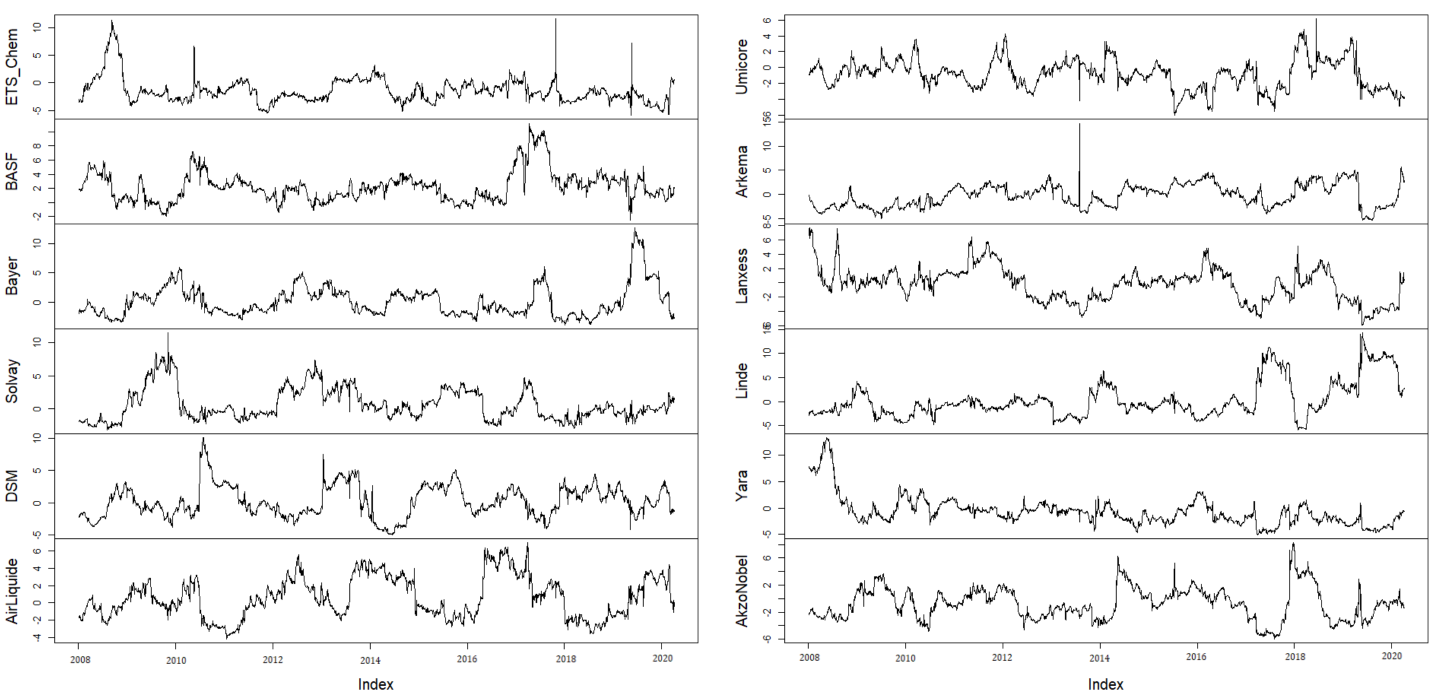
Notes: *Net* volatility spillovers calculated for the EU ETS and firms in the *Airways* sub-sample. The result are obtained using the forecast error variance decomposition of 10-step-ahead forecast horizon and a 200-days rolling window.

FIGURE A.6: Dynamic spillovers, EU ETS and *Cement* companies



Notes: *Net* volatility spillovers calculated for the EU ETS and firms in the *Cement* sub-sample. The result are obtained using the forecast error variance decomposition of 10-step-ahead forecast horizon and a 200-days rolling window.

FIGURE A.7: Dynamic spillovers, EU ETS and *Chemicals* companies



Notes: *Net* volatility spillovers calculated for the EU ETS and firms in the *Chemicals* sub-sample. The result are obtained using the forecast error variance decomposition of 10-step-ahead forecast horizon and a 200-days rolling window.

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