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Volatility spillover between electricity, carbon emissions and green certificates: A Nordic case study

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Abstract: This study investigates volatility spillover between the prices of electricity at Nord Pool, carbon emission allowances in the EU Emissions Trading System (EU ETS) and tradable green certificates (TGC) in the Swedish-Norwegian TGC market. ETS and TGC schemes are market-based policies with the overlapping goals of mitigating greenhouse gas emissions and stimulating sustainable energy investments. A proper understanding of the interactions between these markets is essential for managers of policy and energy technology portfolios. Using a VAR-BEKK model and the Volatility Impulse Response Function (VIRF) methodology, evidence of spillover between all three markets is found. The strongest and most persistent volatility transmission occurs between the prices of electricity and carbon. The VIRF simulations further show that large shocks to electricity and carbon prices increase expected certificate price volatility. These results highlight the importance of considering spillover effects when coordinating market-based climate policies in order to minimise the risks of investing in sustainable energy projects.

Keywords: Volatility spillover, green certificates, carbon pricing, electricity, VIRF.

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Contents

1 Introduction

Policy instruments to stimulate the expansion of renewable energy sourced electricity (RES-E) generation can be designed to either directly increase RES-E production or indirectly by substituting fossil-based production via carbon emissions reduction. An example of the latter is the European Union Emissions Trading System (EU ETS), first initiated in 2005 and to date covering all 27 member states plus Iceland, Liechtenstein and Norway. By means of a ‘cap-and-trade’ mechanism, the scheme aims at achieving the emission abatement targets set forth in the 1997 Kyoto Protocol at lowest possible cost (European Commission, 2015).

Typically, carbon pricing is viewed as a necessary though not sufficient instrument to create suitable investment incentives. A main argument is that carbon pricing tends to under-deliver investments in R&D for new technologies and that a portfolio of different policy instruments hence is required to reach postulated climate policy targets (Blyth et al., 2009; Mazzucato and Semieniuk, 2018). In addition to the region-wide EU ETS legislation, member states of the European Union are therefore obligated to take direct measures to promote RES-E at national level (European Commission, 2009). To comply with the obligation, different types of support schemes that can be characterised as either price-based (e.g. feed-in tariffs) or quantity-based (e.g. quota obligations with tradable green certificates) have become widely adopted by European governments in the past two decades.

In the meantime, a growing body of literature shows that interactions between these multiple policy tools may undermine the overall efficiency of climate policy. The reasoning being that financial support beyond the carbon price signal to stimulate development of RES-E technologies can suppress carbon prices by reducing the level of abatement required from emitting technologies within the scheme (Blyth et al., 2009). A proper understanding of such interactions is essential for policy makers in effectively designing and managing climate policy portfolios, as well as for investors potential to forecast future profits of an energy project. The purpose of this study is to further the empirical research on the subject by in particular investigating the price signals between the EU ETS and the Swedish-Norwegian Tradable Green Certificate (TGC) scheme, two market-based climate policies currently active in the Nordic power market.

The Nordic power system provides an interesting case study for several reasons. Primarily, in accordance with the initiatives behind the EU ETS legislation, the European Commission (2013) recommends using market-based support schemes to promote RES-E. Only few such schemes remain in place today and many countries have or plan to deviate from those and transition to price-based schemes. This makes the Swedish-Norwegian TGC market the most extensive TGC scheme currently active in Europe.

In addition, after initially being introduced in Sweden in 2003 it was later expanded to include Norway in 2012, thereby becoming the first and only international market of its kind in Europe (Schusser and Jaraitė, 2018). As such, Scandinavian electricity producers operate in a competitive and international market context, as the Nordic wholesale electricity market is deregulated since 1996 where trades for the Nordic and Baltic regions take place at Nord Pool. Hence, the dynamics of the large and highly integrated Nordic power system may provide valuable information in the prospect of a future system for EU as a whole.

Furthermore, while the interaction between these markets has been researched quite extensively from a theoretical perspective, the empirical literature is still thin. To my knowledge, the only existing econometric studies that empirically investigate the interaction between the EU ETS and TGC markets are Fagiani (2014) and Schusser and Jaraitė (2018). However, these studies focus on co-movements of prices in their first moments, whereas the objective in this study is to investigate their second-moment interrelations. Doing so is relevant because ETS and TGC schemes both are quantity-based policies, meaning that the supply of carbon emission allowances and the demand for certificates, respectively, are politically determined while the price of these tradable assets are decided at the market. This stands in contrast to price-based schemes where the regulator typically ensures a certain amount of cash flow to RES-E generators by fixing the support level for a sufficient time period ahead.[1]

Quantity-based schemes thus expose power producers to greater risk as they, besides varying electricity prices, also face uncertainty in certificate and carbon prices; While these markets may be volatile on their own, volatility can 'spill over' to the other markets, exacerbating the overall uncertainty over future benefits of an energy project. Examining the volatility formations in these markets is thereby important for a deeper understanding of, and the consequences thereof, interactions between energy policies.

The paper is organised as follows. Following this introduction, a short description of the functioning of the EU ETS and the Swedish-Norwegian TGC scheme is provided in Section 2. Section 3 reviews the existing literature on interactions between such policy instruments and volatility spillover in energy markets. The methodological approaches are discussed in Section 4, consisting of the multivariate GARCH framework and the Volatility Impulse Response Function (VIRF) methodology. The sample of weekly price data used in the study is described in Section 5. Finally, the results are presented, discussed, and summarised in Sections 6 and 7.

[1]Similarly, a carbon tax fixes the price on carbon emissions for fossil-based electricity generation.

2 Policy background

2.1 Functioning of the EU ETS and the Swedish-Norwegian TGC market

Overall, the principals of the EU ETS and the Swedish-Norwegian TGC legislations are alike. The 'cap' in the cap-and-trade system puts an upper limit to the total amount of CO_2 equivalent allowed to be emitted at the EU level. The size of the cap translates into a certain number of emission allowances available in the system, each giving the right to emit one tonne of CO_2 equivalent into the atmosphere. Every year, a small number of allowances are given for free to certain participants while the majority are sold, primarily through auctions.[2,3] At the end of the year, participants must hold and surrender allowances in proportion to their annual emission level, or face a penalty fee. Firms with an insufficient amount of allowances in relation to their emission level can either take measures to reduce their emissions or buy allowances at the market. As the cap is gradually decreased over time, so is the number of allowances available in the system, ensuring that they maintain a financial value (European Commission, 2015).

Similarly, in the TGC market, the government sets the target of renewable energy to be reached by imposing quota obligations on some parties in the power market, mainly electricity-distribution companies and large energy intensive industries. The quota corresponds to a certain share of the total electricity sold or consumed that must originate from renewable sources and is met by purchasing certificates, or face a penalty fee. Each month, the state issues certificates to RES-E generators, one per megawatt hour (MWh) of electricity produced. These are then traded at the market, either bilaterally between producers and quota obligated parties or through stock brokers, ensuring an additional source of revenue apart from the wholesale price of electricity to RES-E producers. The Swedish and Norwegian quota levels are calibrated to stimulate the expansion of RES-E generation in accordance with the postulated common goal of reaching 28.4 terawatt hours (TWh) new RES-E production by 2020.[4] The joint market is planned to last until 2035, while Sweden recently decided to extend the duration of the market domestically to 2045 (Swedish Energy Agency and NVE, 2018).

As such, both policy instruments exploit the market mechanism to create incentives for a continuous emissions abatement and sustainable project development. This means that the demand side and the supply side in the EU ETS and the TGC market, respectively, are dynamic and affected by both natural short term fluctuations in weather conditions and by factors determining the demand for electricity (Koenig,

[2]Prior to the year 2013 this relation was reversed, with the great majority of allowances being allocated for free.

[3]Apart from some minor exceptions, the power sector is subject to 100% auctioning since 2013.

[4]The target was successfully reached in 2019.

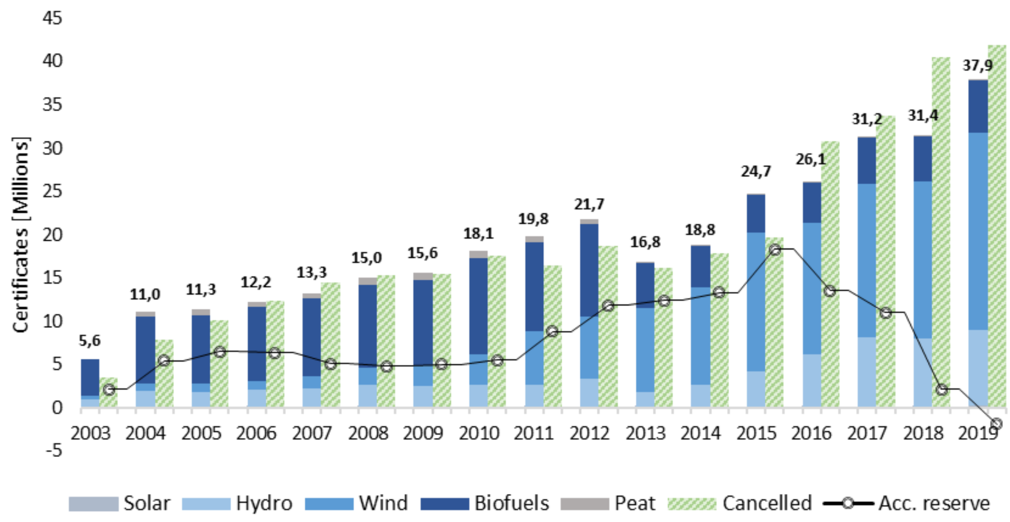

Fig. 1: Annually issued, cancelled and banked certificates in the Swedish-Norwegian TGC market. Source: Cesar (`https:cesar.energimyndigheten.se`) & Swedish Energy Agency and NVE (2020).

2011; Schusser and Jaraitė, 2018). In attempt to dampen the effect of the former on price volatility, a banking mechanism was established in the TGC market, allowing participants to store certificates for use in later years. Fig. 1 depicts annually cancelled and issued certificates per technology along with the total number of issued certificates, as well as the accumulated reserve in the Swedish-Norwegian TGC market. Evidently, both supply and demand has been gradually increasing over time with demand exceeding supply in recent years, resulting in a sharp decline in the accumulated reserve.

The EU ETS is divided into different trading phases with slightly different regulatory design. The first phase ran between 2005-2007 and was viewed as a pilot phase, used to test price formation in the carbon market and establishing the necessary monitoring infrastructure. During this phase, prices were extremely volatile and dropped to near zero in 2007 after the announcement of an oversupply of emission allowances in the system. Phase II ran between 2008-2012 and the third and current phase runs between 2012-2020. The market continues with no end date beyond phase III. Only intra-phase banking was allowed during phase I, such that unused allowances could not be carried over to phase II. This restriction was abandoned in phase II, allowing allowances to be stored and carried over to the next phase. Since both green certificates and emission allowances can be traded either through spot or futures contracts, these banking mechanisms connect spot and future prices via arbitrage considerations (European Commission, 2015; Koenig, 2011).

3 Literature review

3.1 Theoretical studies

Several studies have theoretically analysed how the combination of a carbon and green certificate market affects prices and renewable provision in power markets. Early work includes Amundsen and Mortensen (2001), who formulate a basic static equilibrium model for the Danish electricity market with both green certificates and carbon emission allowances. Their model shows that (under autarky) harsher constraints on carbon emissions will lower certificate prices and the profits to RES-E producers in both the short and the long run. To understand this result, an explanation of the *merit order* is in place.

Koenig (2011) describes how the typical European power producer has a generation plant portfolio, which may consist of both fossil-fuelled and renewable technologies. Relative marginal generation costs will determine which plant in the portfolio that produces during times of baseload and peakload electricity demand.[5] Plants are therefore ranked in order of ascending marginal generation cost - the merit order, and profit maximising producers will start producing from the plant with lowest marginal cost. As demand increases, plants are added following the order of merit. Consequently, the generation cost of the last plant in the merit order to be dispatched (the 'marginal plant') will set the price of wholesale electricity. Since this plant typically is fossil-fuelled, lower thermal efficiency and higher prices of fuel or carbon emissions will rise wholesale electricity prices.

It follows that in the short run when electricity demand is assumed to be fixed, a tighter emission constraint (i.e. reduced supply of carbon allowances) will push up wholesale electricity prices as the marginal cost of carbon-based generation increases as carbon prices rise. This will lower the relative price of renewable provision such that fossil-based power generation is substituted by renewable generation, in turn causing certificate prices to fall as the supply of RES-E increases. Renewable producers are then faced with a scenario of higher wholesale electricity prices but lower certificate prices, giving opposite effects on profits. Amundsen and Mortensen (2001) show, however, that the net effect is negative, leading to reduced investments into new RES-E capacity in the long run.

Similar conclusions are reached by Amundsen and Nese (2009) and Widerberg (2011), examples that extend Amundsen and Mortensen's model with more realistic

[5] Baseload is the minimum demand in the power system. Peakload refers to peak electricity demand. Baseload power plants are typically characterised by low long-term marginal costs and high generation reliability. In the Nordic system, these have historically primarily been hydro, nuclear and coal plants (Koenig, 2011; Fell, 2010).

assumptions for the Nordic context. Amundsen and Nese find that increasing carbon prices lower certificate prices and RES-E production in the long run both under autarky and when allowing for trade in electricity and certificates between two countries. Widerberg considers a scenario even closer to the Swedish-Norwegian agreement by extending an already existing domestic TGC market to a two-country model with a common TGC, power, and carbon emissions market. She finds that, irrespective of the underlying assumptions, an increase in carbon prices lowers both renewable and fossil-based power provision in the short as well as in the long run.

Rathmann (2007) concentrates instead on the impact on wholesale electricity prices of interactions between support schemes for RES-E and the EU ETS. Indeed, he notes that increasing carbon prices will rise electricity prices while a functioning subsidy should have the reversed effect. The latter being a direct effect of a change in the merit order as fossil-fuelled technologies are replaced by renewables with close to zero marginal costs. He further shows that there is an additional, indirect effect of this substitution due to the interaction between the policies; As the fossil-based generation decreases, so will the demand for emission allowances and consequently the carbon price falls, reducing electricity prices even further and hence also producer profits.

These studies indicate that the simultaneous existence of a carbon and TGC market may disrupt the aim of the latter in stimulating the expansion of green technologies, even though emissions abatement and consumption of the required *share* of renewable electricity may be reached. On the other hand, since they are all based on static analysis, they are unable to address the role of risk and uncertainty. Blyth et al. (2009) argue that these factors are crucial when considering interactions between carbon pricing and support for RES-E. This is because risk both affects investment decisions, and is affected by market design - accentuating the relevance of this study. Policy makers therefore need to take risk into account when designing market-based policies and contemplate how investors respond to price signals, the authors reason. By use of a dynamic stochastic model and simulations, they show that supporting large-scale deployment of mature technologies can be sub-optimal as it tends to suppress carbon prices, whereas support for early stage R&D may reduce both total abatement costs and carbon price risk.

3.2 Empirical studies

Turning to the empirical econometric studies that analyse price formation in the Nordic power market, Brännlund et al. (2012) find that electricity consumer prices historically (1970-2010) have been positively correlated with coal prices and economic activity, and negatively correlated with temperatures, nuclear power generation and water reservoir levels. They further identify a structural break in 2006 which they connect to the introduction of the EU ETS that led to higher coal prices in the Nordic power system, and in turn spilled over to electricity prices. Accordingly, Fell (2010) uses a vector error correction model and an impulse response analysis to confirm that Nordic wholesale electricity prices are cointegrated with EU ETS emission allowances, coal and natural gas prices, and that a positive exogenous shock to allowance prices positively impacts electricity prices in the short run.

Considering policy interactions, Fagiani (2014) also employs the error correction methodology to investigate price formation in the Swedish-Norwegian and the UK TGC markets. In accordance with the theoretical expectation, he identifies a negative long-run relationship between the Swedish-Norwegian certificate price and energy prices (coal, natural gas and EU ETS emission allowances), while the UK certificate price is related to an industrial production index. Meanwhile, he cannot find any short-term relationship between the variables. The short-term dynamics between the Swedish-Norwegian TGC market, the EU ETS and Nord Pool is the focal point in Schusser and Jaraitė (2018). They use weekly data for the years 2005-2015 and estimate a VAR model and conduct an impulse response analysis. Interestingly, the authors find a small but *positive* short-term impact on certificate prices following a positive shock in carbon prices, and conclude that the EU ETS and the TGC scheme do not seem to interfere with each other's price formation.

All studies mentioned thus far are focused to first-moment interrelations, while second-order co-movements have received relatively little attention in research on price formation in energy markets. Fagiani and Hakvoort (2014) estimate a GARCH model and apply endogenous structural break tests to confirm that announcements of future regulatory changes negatively impact the Swedish-Norwegian TGC market by creating regimes of increased volatility. However, they use a univariate GARCH model and hence cannot explicitly model cross-market interdependicies.

On that account, Mansanet-Bataller and Soriano (2009) provide the first econometric study that investigates volatility spillover between carbon and energy markets. Using a multivariate GARCH framework, the authors find evidence of volatility spillover to the EU ETS from natural gas and oil markets. Similar results are found in Koenig (2011) and Green et al. (2018), which concentrate on volatility transmission between the EU ETS and energy markets in the UK and Germany, respectively. The latter study uses a similar, albeit more sophisticated, econometric approach to the one adopted here by estimating a VAR-BEKK model and utilising the volatility impulse response methodology proposed by Hafner and Herwartz (2006). This methodology has been used for analysis of energy markets by Le Pen and Sévi (2010) and Jin et al. (2012)

as well. Meanwhile, I believe that this is the first attempt to uncover the volatility interdependences between green certificate, carbon emissions, and power markets.

4 Methodology

I employ the multivariate GARCH methodology and conduct a volatility impulse response analysis to investigate the volatility dynamics of the Nordic power market (Nord Pool), the EU ETS and the Swedish-Norwegian TGC market. The preceding overview of the recent literature suggests that these are connected through additional markets. However, as will be discussed below, the empirical estimation quickly gets overly complex as the number of time series increases. The analysis is therefore delimited to focusing on the three aforementioned markets as understanding the interrelations between those is the primarily research interest in this study. Deepening the analysis to include additional, presumably connected, markets is left as a topic for future research.

Analogous to the univariate GARCH process, the estimation of the multivariate GARCH framework consists of two sequential steps. First, an appropriate model of the conditional mean should be specified. Thereafter, the residuals obtained from this model are used as inputs to model the conditional variances and covariances. The succeeding two subsections will describe in detail the econometric techniques utilised to estimate these models, followed by a description of the volatility impulse response methodology.

4.1 Estimation of the conditional means

Following the standard in previous literature, I model the first moment of the multivariate time series as a vector autoregression (VAR) of order p. Thus, each return series is treated symmetrically, assumed to be a function of both its own past returns and the past returns of the other two commodities:

$$r_t = \eta + \Sigma_{j=1}^{p} \Phi_j r_{t-j} + \epsilon_t \qquad\qquad \epsilon_t|\Omega_{t-1} \sim N(\mathbf{0}, H_t) \tag{1}$$

where r_t is the 3×1 vector of returns, i.e. $r_t = (r_{1,t}, r_{2,t}, r_{3,t})'$ with 1 = electricity, 2 = carbon and 3 = certificate, η is a 3×1 vector of constants, Φ_j are 3×3 matrices of coefficients for lag $j = 1, ..., p$ and ϵ_t is a 3×1 vector of serially uncorrelated, zero-mean error terms with conditional variance-covariance matrix H_t.

4.2 Estimation of the conditional covariances

In theory, the generalisation of the univariate GARCH(p,q) model (Bollerslev, 1986) to its multivariate counterpart is straightforward. Assuming that ϵ_t in Eq. (1) is conditionally heteroskedastic such that $\epsilon_t = H_t^{1/2} z_t$, with $z_t \sim i.i.d.(\mathbf{0}, I)$, the general so called vec representation of the multivariate GARCH(1,1) model can be defined as:

$$\text{vech}(H_t) = c + A_1^* \text{vech}(\epsilon_{t-1}\epsilon_{t-1}') + G_1^* \text{vech}(H_{t-1}) \tag{2}$$

where vech(.) is the operator that stacks the lower triangle of a symmetric $k \times k$ matrix into a $k^* = k(k+1)/2$ vector, c is a vector of k^* coefficients, and A_1^* and G_1^* are matrices containing $(k^*)^2$ ARCH and GARCH parameters, respectively. Noteworthy is that even in the simplest bivariate case with $k = 2$, there are as many as 21 parameters that characterise this model.

In empirical work, imposing some sort of parameter restriction on the full vec representation of H_t in Eq. (2) is therefore often necessary, where the Diagonal vec, Constant Conditional Correlation (CCC) and Baba-Engle-Kraft-Koner (BEKK) specifications are among the most frequently used (Hafner and Herwartz, 2006; Enders, 2014). The Diagnonal vec restricts the off-diagonal elements of H_t to be zero such that cross-market correlations are not allowed. The CCC allows for cross-market correlations but restricts them to be constant over time, an assumption Koenig (2011) finds to be violated in energy markets. Engle (2002) also proposed an extension of the CCC model, the Dynamic Conditional Correlation (DCC) model, to allow for time-varying co-movements. However, the DCC imposes stronger parameter restrictions compared to the BEKK specification and models conditional correlations rather than covariances. This leaves the BEKK specification to be the most suitable choice for the objectives in this study, as it allows for a direct interpretation of the parameters in terms of second-moment spillovers. In addition, it has the benefit of being positive-definite by construction since all parameters enter the model via quadratic forms.

The symmetric BEKK(1,1) model (Engle and Kroner, 1995) considered in this study takes the following form:

$$H_t = C'C + A_1' \epsilon_{t-1}\epsilon_{t-1}' A_1 + G_1' H_{t-1} G_1 \tag{3}$$

where H_t is the 3×3 conditional variance-covariance matrix, C is a 3×3 matrix of constants restricted to be upper triangular, ϵ_{t-1} is the 3×1 vector of error terms in Eq. (1), and A_1 and G_1 are 3×3 unrestricted matrices of ARCH and GARCH parameters. While the sign of the parameters in the BEKK model have no straightforward interpretation given their non-linear appearance, the diagonal elements of A_1 effectively measure the effect of own-market volatility shocks, while the off-diagonal elements measure the effect of cross-market volatility shocks. Similarly, the diagonal and off-diagonal elements of G_1 measure persistence in own-market and cross-market volatility. Covariance stationarity of the model requires all eigenvalues of $(A_1 \otimes A_1) + (G_1 \otimes G_1)$ to be less than one in modulus, where $\otimes$ is the Kronecker Tensor product.

The BEKK model is a restricted version of the vec representation in Eq. (2), and in this setting with $k = 3$ requires estimation of 24 parameters. These are obtained using maximum likelihood. Under the assumption of independent and conditionally multivariate-normally distributed innovations, the log likelihood function of the joint distribution is given by:

$$L(\theta) = -\frac{T}{2}\ln(2\pi) - \frac{1}{2}\sum_{p+1}^{T}(\ln|H_t| + \epsilon_t' H_t^{-1}\epsilon_t) \tag{4}$$

where θ are the estimated parameters, $|H_t|$ is the determinant of H_t, T is the number of time series observations, and the lower limit of the summation is set to $p+1$ given the first p observations owing to estimating the VAR model. Note that if the true conditional distribution of ϵ_t is not Gaussian, which is often the case for financial assets, Eq. (4) is the *quasi*-likelihood function and maximisation gives the quasi maximum likelihood (QML) estimator. Regardless, the QML estimator is consistent and asymptotically normal which justifies its application despite any known non-normality (Engle and Kroner, 1995; Hafner and Herwartz, 2006).

To maximise the likelihood function, numerical techniques are utilised. As suggested by Engle and Kroner (1995), I begin by estimating a diagonal BEKK model to obtain a set of starting values for estimation of the unrestricted model in Eq. (3), employing the BFGS (Broyden-Fletcher-Goldfarb-Shanno) algorithm. Computations of the full model are performed using the **mgarch** package implemented in R language.

4.3 Volatility impulse response analysis

4.3.1 Identification of independent shocks

While cross-market spillover effects are effectively identified by the BEKK model, the contemporaneous correlations typically present in a multivariate framework implies that the error components in ϵ_t cannot be interpret as shocks coming from independent sources. To disentangle the effect of an independent shock originating in one market, I continue to estimate the Volatility Impulse Response Function (VIRF) developed by Hafner and Herwartz (2006). The VIRF extends Koop et al. (1996)'s generalised impulse response function to the general multivariate GARCH framework.

Hafner and Herwartz (2006) reason that shocks, which they refer to as 'news', are inherently independent over time and that news appearing in one time series is independent from news in another series if they appear at the same time. This assumption allows the VIRF to be derived from the underlying data generating process by defining news to appear in the i.i.d. innovation z_t. In practice, a Choleski decomposition is generally employed to identify z_t. However, to avoid dependence on the ordering of variables in the system, Hafner and Herwartz (2006) suggest using a Jordan decomposition of H_t to obtain the symmetric matrix $H_t^{1/2}$:

$$H_t^{1/2} = \Gamma_t \Lambda_t^{1/2} \Gamma_t' \tag{5}$$

where $\Lambda_t = \mathrm{diag}(\lambda_{1t}, \lambda_{2t}, \lambda_{3t})$ is the diagonal matrix containing the eigenvalues of H_t and $\Gamma_t = (\gamma_{1t}, \gamma_{2t}, \gamma_{3t})$ is the 3×3 matrix of the corresponding eigenvectors. Thus, a vector of independent shocks can be identified as:

$$z_t = H_t^{-1/2} \epsilon_t \tag{6}$$

4.3.2 Definition and analytical derivation of the VIRF

The VIRF is defined as the expectation of volatility conditional on an initial shock and history subtracted by a baseline expectation that conditions on history only:

$$V_h(\Omega_{t-1}, z_t) = \mathrm{E}[\mathrm{vech}(H_{t+h})|\Omega_{t-1}, z_t] - \mathrm{E}[\mathrm{vech}(H_{t+h})|\Omega_{t-1}] \tag{7}$$

where z_t is the initial shock, defined by Eq. (6), hitting the system at time t, Ω_{t-1} is the observed history up to time $t-1$ and $V_h(\Omega_{t-1}, z_t)$ is the k^* vector of the impact of z_t on the h-step ahead conditional covariance matrix. According to Engle and Kroner (1995), every BEKK model has a unique and equivalent vec representation, meaning that the VIRF can be applied to the vectorised version of the BEKK model in Eq. (3). Since H_t is a symmetric matrix, I use this vec representation to eliminate the duplicated entities.[6] In this setting with $k^* = 6$, there are three elements in $V_h(\Omega_{t-1}, z_t)$ representing the responses in variances and three elements representing the responses in covariances.

Hafner and Herwartz (2006) derive analytical VIRF expressions for the general symmetric multivariate GARCH model. Applied to the BEKK(1,1) and then the vec

[6] Formally, the A_1 and G_1 matrices in Eq. (3) are transformed into their vec representation accordingly to Eq. (2) as $A_1^* = L_k(A_1^{'} \otimes A_1^{'})D_k$ and $G_1^* = L_k(G_1^{'} \otimes G_1^{'})D_k$, where L_k is the elimination matrix such that $\mathrm{vech}(Z) = L_k \mathrm{vec}(Z)$ and D_k is the duplication matrix such that $\mathrm{vec}(Z) = D_k \mathrm{vech}(Z)$, for any symmetric $k \times k$ matrix Z.

representation, the one-step ahead VIRF is thereby easily obtained as:

$$\begin{aligned} V_1(\Omega_{t-1}, z_t) &= A_1^* D_k^+ (H_t^{1/2} \otimes H_t^{1/2}) D_k \mathrm{vech}(z_t z_t' - I_k) \\ &= A_1^* \{\mathrm{vech}(H_t^{1/2} z_t z_t' H_t^{1/2}) - \mathrm{vech}(H_t)\} \end{aligned} \tag{8}$$

where H_t is the initial conditional covariance matrix at time t, I_k is the identity matrix, D_k is the duplication matrix previously defined and D_k^+ its Moore-Penrose inverse. For any $h \geq 2$ the VIRF is given as:

$$\begin{aligned} V_h(\Omega_{t-1}, z_t) &= (A_1^* + B_1^*)^{h-1} A_1^* D_k^+ (H_t^{1/2} \otimes H_t^{1/2}) D_k \mathrm{vech}(z_t z_t' - I_k) \\ &= (A_1^* + B_1^*) V_{h-1}(\Omega_{t-1}, z_t) \end{aligned} \tag{9}$$

Eq. (9) indicates the following properties of the VIRF, with the first being analogous to the traditional analysis of the conditional mean in linear systems as opposed to the others:

1. The decay or persistence of shocks in the VIRF is given by the moving average matrices $(A_1^* + B_1^*)^{h-1} A_1^*$.
2. The VIRF is an even function of the shock, such that $V_h(z_t) = V_h(-z_t)$.
3. The response is non-linear in the size of the shock. Specifically, the VIRF is not homogeneous of any degree.
4. The VIRF depends on the history of the process through the volatility state H_t at the time when the shock occurs.

4.3.3 Empirical application

Several applications of the VIRF method are possible depending on how the shock and baseline in Eq. (7) are defined. One alternative is to consider a specific observed shock and history in the time series, and then use the estimated ϵ_t and H_t to obtain standardised residuals z_t for which the VIRF can be calculated. Another is to consider a random shock while conditioning on an observed historical baseline. Following closely to Green et al. (2018), this study adopts the latter approach and uses the value-at-risk estimation to obtain a specific level of shock drawn from the underlying distribution of each return series. Here, I consider the 95% quantile, i.e. a relatively large but less frequently occurring exogenous price shock originating in one of the markets, and investigate the cross-market volatility transmission.

In other words, I specify the 'vector of news', z, that gives rise to the system-wide shock $\epsilon_t = H_t^{1/2} z$ traced by the VIRFs in Eqs. (8) and (9) to have one non-zero element and two zero elements:

$$z = (z_1, 0, 0)'$$
$$z = (0, z_2, 0)'$$
$$z = (0, 0, z_3)'$$

where $i = 1, 2, 3$ denotes news appearing in the electricity, carbon, and certificate return series, respectively.[7] Note that, despite the zero elements in z, all elements in the vector defined by the first term on the second line in Eq. (8) are non-zero and time varying. Consequently this allows for an investigation of how exogenous shocks propagate through the multivariate system. As such, this application corresponds to a scenario where the current state of volatility can be observed and the change in future volatility given a probable, yet unobserved, shock can be projected. Such an forward looking approach is likely to be of greater value to regulators and investors in risk assessment of policy and technology portfolios.

Moreover, recall that the VIRF depends on the volatility state of the system at the time of the shock, implying that its shape will differ depending on the selected point in the time series the shock is introduced. For this reason, I choose to consider an average VIRF, calibrated from introducing shocks at each point within the sample period, to obtain a general picture over how an exogenous shock can be expected to impact volatility dynamics in the considered markets. To calculate the VIRFs, I therefore proceed as follows. First, I construct shocks $\epsilon_t = H_t^{1/2} z$ for each time series and week $t = 1, ..., T$ in the sample, using the above defined news vectors and the square root of the estimated covariance matrices obtained from the Jordan decomposition. Second, I calculate VIRFs for each week over the horizon $h = 1, ..., 52$, i.e. one year ahead. Lastly, I average the resulting T VIRFs for each h, giving a final 6×52 matrix of averaged VIRFs for each series.

5 Data

The data used in the study is comprised of weekly average spot prices of Nordic wholesale electricity, EU ETS emission allowances and green certificates in the Swedish-Norwegian TGC market, converted into log-returns; $r_t = \ln(P_t/P_{t-1})$. The sample period spans from the last week of January 2009 to the last week of December 2019, covering in total 569 observations. It is restricted to this starting point to avoid the

[7] Under the assumption of normality, z_i simply corresponds to the 95% quantile of a standardised normal distribution, such that $z_1 = z_2 = z_3 = 1.645$.

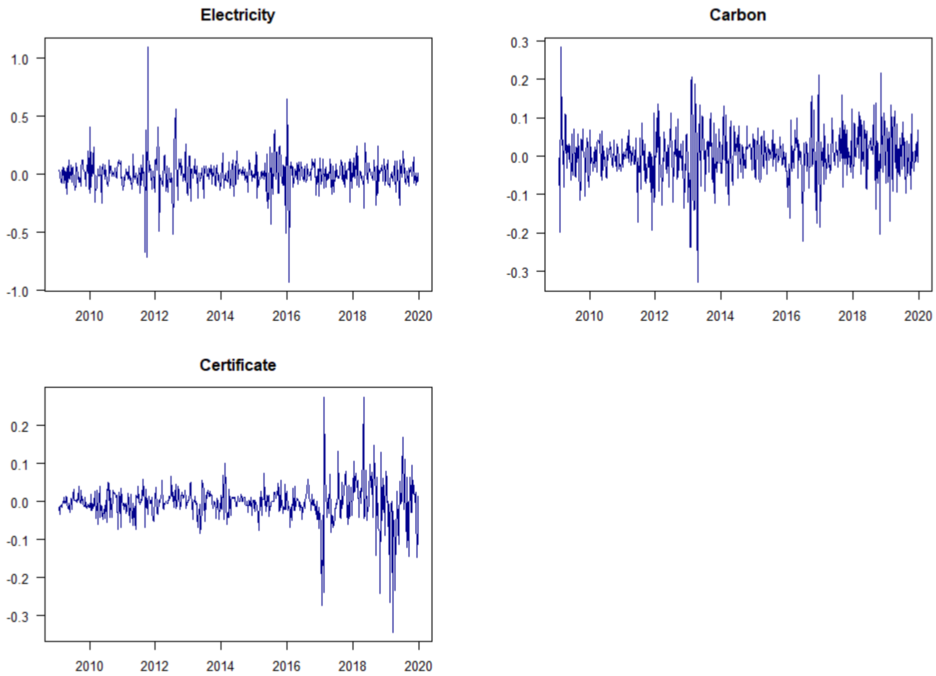

Fig. 2: Weekly averages of log-returns spanning from the first week of February 2009 to the last week of December 2019.

abnormal price drop experienced in the initial phase of the EU ETS as discussed in Section 2, after which spot prices recovered first at the end of January 2009.

The day-ahead electricity price (SEK/MWh) is collected from the Nordic power exchange Nord Pool. It corresponds to the average price of all bidding zones in the Nordic-Baltic market and is the main reference for traded long term electricity contracts. Certificate prices (SEK/MWh) are collected from the brokerage firm Svensk Kraftmäkling, the largest and most liquid market place for green certificates as well as the only public price recording in the Swedish-Norwegian TGC market. Svensk Kraftmäkling has brokered certificates since the market introduction in 2003, and weekly and monthly average prices for the spot and futures markets are readily available at their webpage. Finally, the average settlement price of EU ETS emission allowances (SEK/-tonne CO_2) traded at the European Energy Exchange is collected from Datastream. European Energy Exchange serves as the transnational common auction platform for emission allowances for most participating countries in the EU ETS.

The return series are illustrated in Fig. 2, which indicates no-constant variances and presence of volatility clustering in all markets. The largest peaks are observed for electricity with weekly price changes occasionally being as large as 70-100%, reflected by the many factors influencing supply and demand in the Nordic power system. Carbon prices have been quite volatile throughout the sample period. Regarding the TGC market, one observation of particular importance for the empirical estimation can be

Table 1: Descriptive statistics & stationary tests for weekly returns.

	Electricity	Carbon	Certificate
Panel A: Sample period 2009-2016			
Nr. of obs.	412	412	412
Mean	-0.001	-0.002	-0.003
Minimum	-0.929	-0.329	-0.083
Maxiumum	1.098	0.285	0.101
Std. dev.	0.151	0.067	0.026
Skewness	0.090	-0.345	-0.092
Excess kurt.	13.088	3.040	0.944
ADF test[a]	-16.326	-14.478	-12.223
PP test[b]	-20.902	-17.357	-15.883
KPSS test[c]	0.019	0.090	0.071
Panel B: Sample period 2017-2019			
Nr. of obs.	156	156	156
Mean	0.002	0.010	-0.006
Minimum	-0.293	-0.203	-0.344
Maxiumum	0.274	0.217	0.274
Std. dev.	0.094	0.064	0.085
Skewness	-0.146	-0.123	-0.569
Excess kurt.	0.868	1.023	3.141
ADF test[a]	-10.406	-10.255	-7.758
PP test[b]	-13.252	-15.620	-9.691
KPSS test[c]	0.073	0.207	0.192

[a, b] 99% critical value is -3.434
[c] 99% critical value is 0.739

made, namely a shift in the long run variance at the beginning of 2017 when prices entered a considerably more volatile regime. Indeed, it is found that estimation using all observations in the sample results in an unstable GARCH model, indicated by some eigenvalues of the sum of the Kronecker products being larger than unity. In consequence, the VIRF displays an explosive behaviour for the TGC market.

As discussed in Section 2, Fig. 1 implies changing market dynamics in the TGC scheme in recent years, with excess demand and drastic drops in the accumulated reserve. This may have induced uncertainty regarding future supply and demand, resulting in more volatile prices. Taking into consideration the findings of Fagiani and Hakvoort (2014), another plausible explanation could be the extended political deliberations and many regulatory decisions lately taking place on the Swedish part of the scheme. In this regard, 2016 was a particularly turbulent year due to the adoption of a new energy policy in Sweden, aiming to archive a 100% renewable energy provision by 2040. This resulted in the decision to extend the duration of the TGC market domestically, as well as the withdrawal of an earlier suggested stop-date for when new plants should no longer be entitled to participate in the TGC scheme as the market moves towards its termination (Swedish Energy Agency, 2016).

Put together, this suggests that dividing the analysis into subperiods is not only necessary for modelling purposes but also enables an interesting possibility to detect any changes in volatility transmission during different phases of the support scheme. To be specific, I focus the analysis to two subperiods, the first ranging from the first week of February 2009 until the last week of December 2016, and the second ranging from the first week of January 2017 until the last week of December 2019.

Table 1 presents summary statistics for each of these subsamples. As expected, all return series exhibit excess kurtosis and skewness and hence do not comply with the normal distribution assumption. Stationarity is confirmed based on the Augmented Dickey Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test results, also presented in the table. The large ADF and PP test statistics suggest that the null hypothesis of a unit root is strongly rejected for all series and, accordingly, the small KPSS statistics indicate that the null hypothesis of stationarity cannot be rejected for any series.

6 Empirical results

6.1 Parameter estimates for the conditional means and covariances

The parameter estimates for the VAR models of the conditional means are reported in Table A1 in the appendix. The appropriate lag length p was determined based on the Akaike, Schwartz and Hannan-Quinn information criteria, as well as the Final prediction error. A lag length equal to one is selected by two out of four of those for the first subsample, and by all four for the second subsample. In the interest of parsimony, the VAR(1) specification was thereby selected for both subperiods as autocorrelation plots (see Fig. A1) indicate that this specification is sufficient to rule out any problematic serial correlation in the standardised residuals. The figures in Table A1 show that certificate and carbon returns are related to own-market past returns but not cross-market passed returns for this model specification. Meanwhile, in line with the theoretical expectation and findings in previous research, a positive first-moment spillover effect from carbon to electricity prices is identified in the first subperiod.

Importantly, autocorrelation plots over the squared standardised residuals retrieved from the VAR models confirm the presence of ARCH effects, making an analysis of the conditional covariances worth while. For that purpose, a BEKK(1,1) model was specified for each of the two subperiods, and the resulting parameter estimates are presented in panels A and B of Table 2. With exception for g_{33} in panel A, all diagonal elements of the A_1 and G_1 matrices are statistically significant at least at the 5% level.

Table 2: BEKK(1,1) estimates for the conditional covariances.

Panel A: Sample period 2009-2016

c_{11}	0.051***	c_{12}	0.017***	c_{13}	0.002
	(0.006)		(0.003)		(0.003)
		c_{22}	-0.005	c_{23}	-0.006
			(0.014)		(0.012)
				c_{33}	0.024***
					(0.003)
a_{11}	0.734***	a_{12}	-0.051***	a_{13}	0.003
	(0.060)		(0.019)		(0.012)
a_{21}	0.175	a_{22}	0.429***	a_{23}	0.022
	(0.117)		(0.049)		(0.033)
a_{31}	-0.196	a_{32}	-0.264**	a_{33}	0.282***
	(0.294)		(0.128)		(0.078)
g_{11}	0.640***	g_{12}	0.056***	g_{13}	0.005
	(0.040)		(0.013)		(0.014)
g_{21}	-0.352***	g_{22}	0.845***	g_{23}	-0.021
	(0.058)		(0.031)		(0.016)
g_{31}	-0.065	g_{32}	0.076	g_{33}	-0.012
	(0.457)		(0.359)		(0.035)

λ_i

0.964 0.883 0.852+0.103i 0.852-0.103i 0.193 0.188 0.132
0.096+0.029i 0.096-0.029i

Panel B: Sample period 2017-2019

c_{11}	0.050***	c_{12}	0.039**	c_{13}	0.014
	(0.010)		(0.015)		(0.012)
		c_{22}	0.015	c_{23}	-0.029
			(0.059)		(0.124)
				c_{33}	0.037
					(0.106)
a_{11}	0.599***	a_{12}	0.132*	a_{13}	0.080
	(0.111)		(0.075)		(0.076)
a_{21}	0.113	a_{22}	-0.375***	a_{23}	0.014
	(0.142)		(0.112)		(0.146)
a_{31}	-0.329***	a_{32}	-0.041	a_{33}	-0.201**
	(0.115)		(0.078)		(0.100)
g_{11}	-0.371***	g_{12}	0.242**	g_{13}	-0.247
	(0.138)		(0.143)		(0.161)
g_{21}	-0.521**	g_{22}	0.404***	g_{23}	0.292
	(0.222)		(0.118)		(0.331)
g_{31}	-0.020	g_{32}	0.074	g_{33}	0.619***
	(0.229)		(0.083)		(0.127)

λ_i

0.596 -0.468 0.416 -0.222+0.076i -0.222-0.076i 0.211 -0.167
0.156 0.126

Notes: Parameter estimates for C, A_1 and G_1 matrices in Eq. (3), denoted by c_{ij}, a_{ij} and g_{ij} for $i, j = 1$ (electricity), 2 (carbon) and 3 (certificate). a_{ij} and g_{ij} control volatility spillover from j to i for $j \neq i$. λ_i are the eigenvalues of $(A_1 \otimes A_1) + (G_1 \otimes G_1)$. Standard errors in parenthesis. *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

These parameters confirm the presence of high own-market ARCH and GARCH effects in all three markets. The larger sizes of a_{33} and g_{33} in panel B, compared to panel A, is in accordance with the observation from Fig. 2 that certificate prices entered a more turbulent regime with larger volatility clustering after being fairly stable in the first subperiod.

Further, some of the off-diagonal elements are statistically significant, supporting the hypothesis that these assets are connected through their second moments as well. Here, spillover effects between the power market and the EU ETS are most apparent and found to be bidirectional (a_{12}, g_{12}, g_{21}) in both periods. A similar two-way relationship in the first moments of these commodity prices is identified by Schusser and Jaraitė (2018), and Green et al. (2018) find evidence of bidirectional volatility spillover between the German power market and the EU ETS as well.

Meanwhile, spillover channelling to and from the TGC market differs between the subperiods. There is no statistical evidence of a second-moment interrelation between the certificate and electricity series in the first subperiod, whereas a_{31}, controlling volatility spillover from the TGC market to the power market, is large and highly significant in the second subperiod. Also, spillover in the opposite direction (g_{13}) is barely not significant at the 10% level (p-value = 1.53). As emphasised by Schusser and Jaraitė (2018), one reasonable explanation for this could be the characteristics of the Swedish and Norwegian energy mixes. As can be seen in Fig. A2 in the appendix, these countries have been relatively independent of carbon-intensive power generation with hydro and nuclear being the dominant sources. This suggests that the introduction of the TGC scheme had a small effect on RES-E generation and consequently on the price formation at the Nordic power exchange. However, the recent expansion in wind power capacity and thereby increased supply of certificates can plausibly explain the increasing interdependence between the markets over time.

Of particular interest is the statistically significant parameter a_{32} in panel A, controlling volatility spillover from the TGC market to the EU ETS. Indeed, this implies that there may also be undesirable effects of combining market-based climate policies, in terms of exacerbating the uncertainty over future profits to power generators. Intuitively, it is however quite unexpected to find spillover to occur in this direction. Given the relatively small size of the Swedish-Norwegian TGC market compared to the EU ETS, I would rather expect spillover to appear in the opposite direction. Nevertheless, it should be emphasised that the BEKK parameters are associated with spillover coming from all markets.[8] In the next section I will account for such system feedback

[8] For example, performing the intended matrix multiplications of Eq. (3), it can be shown that

using the VIRF methodology. Interestingly, none of the parameters governing spillover between the TGC market and the EU ETS are found to be statistically significant in the second subperiod. Although the small number of 155 observations representing this sample should be taken into consideration, this indicates that these markets may have decoupled in past years.

6.2 VIRF results and analysis

The BEKK-model outputs reported in the preceding section indicate at least a weak second-moment interrelation between all three markets under consideration. To further investigate the strength and persistence in spillover, I proceed to conduct a volatility impulse response analysis. Here, I use the estimated parameters in Table 2 to obtain the conditional covariance matrices and focus the analysis to the two elements in $V_h(\Omega_{t-1}, z)$ representing the cross-market responses in the conditional variances to news z_i appearing in one of the markets. The time profiles of the resulting volatility impulse responses are depicted in Figs. 3 and 4. They have been scaled with respect to the baseline expectation, such that the results can be interpreted as percentage deviations in expected volatility in the shock scenario compared to the base scenario.

Overall, the persistence of shocks is higher in the first subperiod compared to the second. The effect of all shocks in Fig. 4 die out after approximately 8 weeks whereas, for instance, the response in carbon volatility to news in electricity prices cannot be cancelled even after 52 weeks in Fig. 3. This feature is attributable to the fact that several eigenvalues of the sum of the Kronecker products, reported in Table 2, are close to unity in the first subperiod.

One striking phenomenon is that the instantaneous responses to shocks exclusively appear with a negative sign. This suggests that, on average, the expected week-ahead conditional variances are lower when conditioning on the news than when conditioning on history only. It should be reminded here that the baseline expectation is not fixed to zero, as opposed to the typical application in first-moment impulse response analysis (Hafner and Herwartz, 2006). Because the baseline is specified by H_t, which depends on all past realised shocks $\{\epsilon_{t-1}, ..., \epsilon_1\}$, it can be viewed as a shock to volatility itself. Technically then, if the exogenous price shock has a zero, or close to zero, cross-market volatility impact, the corresponding element in $V_1(\Omega_{t-1}, z)$ will according to Eq. (8) be negative. Hence the economic interpretation of a negative VIRF would be that information about an abnormal event in another market does not induce market obs-

the conditional carbon variance is given by: $h_{22,t} = c_{12}^2 + c_{22}^2 + a_{12}^2\epsilon_{1,t-1}^2 + a_{22}^2\epsilon_{2,t-1}^2 + a_{32}^2\epsilon_{3,t-1}^2 + 2a_{12}a_{22}\epsilon_{1,t-1}\epsilon_{2,t-1} + 2a_{12}a_{32}\epsilon_{1,t-1}\epsilon_{3,t-1} + 2a_{22}a_{32}\epsilon_{2,t-1}\epsilon_{3,t-1} + g_{12}^2h_{11,t-1} + g_{22}^2h_{22,t-1} + g_{32}^2h_{33,t-1} + 2g_{12}g_{22}h_{12,t-1} + 2g_{12}g_{32}h_{13,t-1} + 2g_{22}g_{32}h_{23,t-1}$.

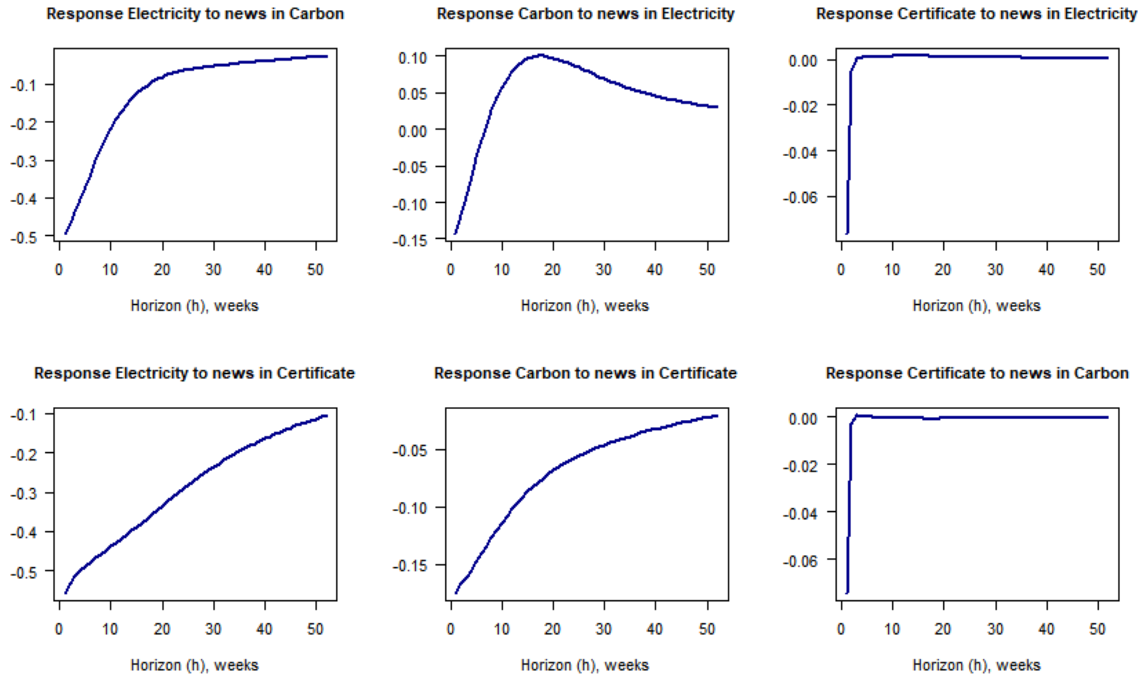

Fig. 3: VIRFs ($p = 0.05$) calculated according to the description in Section 4.3.3 for sample period 2009-2016. The first, second and third columns illustrate the cross-market responses in variance of electricity, carbon and certificate returns, respectively, over a one year horizon.

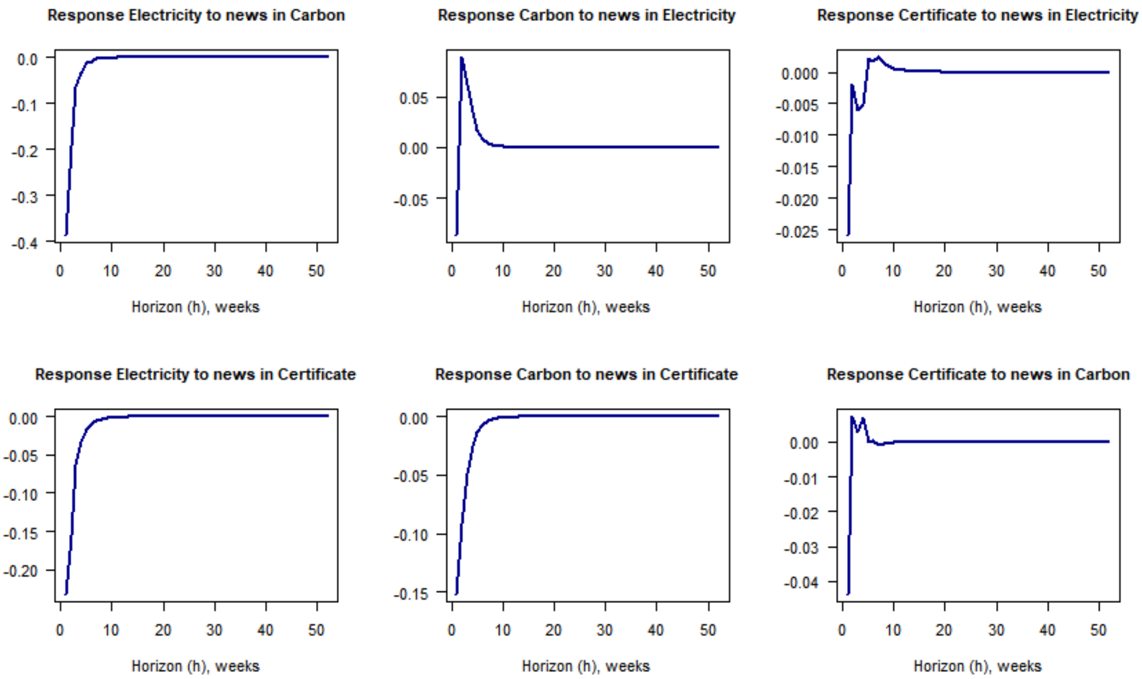

Fig. 4: VIRFs ($p = 0.05$) calculated according to the description in Section 4.3.3 for sample period 2017-2019. The first, second and third columns illustrate the cross-market responses in variance of electricity, carbon and certificate returns, respectively, over a one year horizon.

ervers to revise their expectation of future volatility upwards.

Nevertheless, in some cases a delayed, yet positive, effect of the initial shock is visible. In Fig. 3, the carbon VIRF following news in electricity becomes positive after seven weeks, reaching a peak at 10% in week 18. The impact slowly decays thereafter but remains above zero even after 52 weeks. In Fig. 4, the effect of the same shock peaks at 9% two weeks after the shock hits the system and vanishes after six weeks. Interestingly, the same pattern does not emerge for electricity volatility following news in carbon, with the VIRF being negative and decaying throughout the horizon and sample period. This could be explained by the stronger evidence of spillover from electricity to carbon prices, compared to the reversed direction, inferred from the estimated BEKK parameters. Likewise, the negative or close to zero VIRFs governing the volatility impulse responses between electricity and certificate prices seem reasonable given the rather weak evidence from the BEKK models of a connection between these markets.

Moreover, as expected, these results provide no indications that increased uncertainty in the Swedish-Norwegian TGC market affects volatility expectations in the EU-ETS. Conversely, a marginal but positive increase of about 0.7% in the expected certificate variance in response to news in carbon becomes visible after two weeks in the second subperiod, contrasting the implications from the BEKK estimates.

6.2.1 Alternative shock scenario

The profiles in Figs. 3 and 4 resulted from introducing exogenous shocks with a probability $p = 0.05$ of occurrence. This means that the markets are expected to experience a shock of this magnitude two to three weeks per year. Because of the fairly weak indications of a cross-market response in this scenario, I continue to consider a larger but less probable shock with $p = 0.01$.[9] This corresponds to a shock that is expected a half week per year, or one week every two years. The time profiles of the resulting volatility impulse responses are depicted in Figs. 5 and 6.

Naturally, the positive responses identified in the $p = 0.05$ scenario are now amplified. Most importantly, the response in expected certificate volatility to news in carbon in the second subperiod is significantly larger, peaking at 5% three weeks ahead. Now, a small impact on expected certificate volatility, of about 3%, three weeks after a news event in the power market appears in the second subperiod as well. The response in carbon volatility to news in electricity in the first subperiod is more immediate, with the VIRF turning positive after three weeks in Fig. 5. In addition, a delayed but sizable

[9]In other words, I now consider the 99% quantile such that the news vectors are revised using $z_1 = z_2 = z_3 = 2.326$.

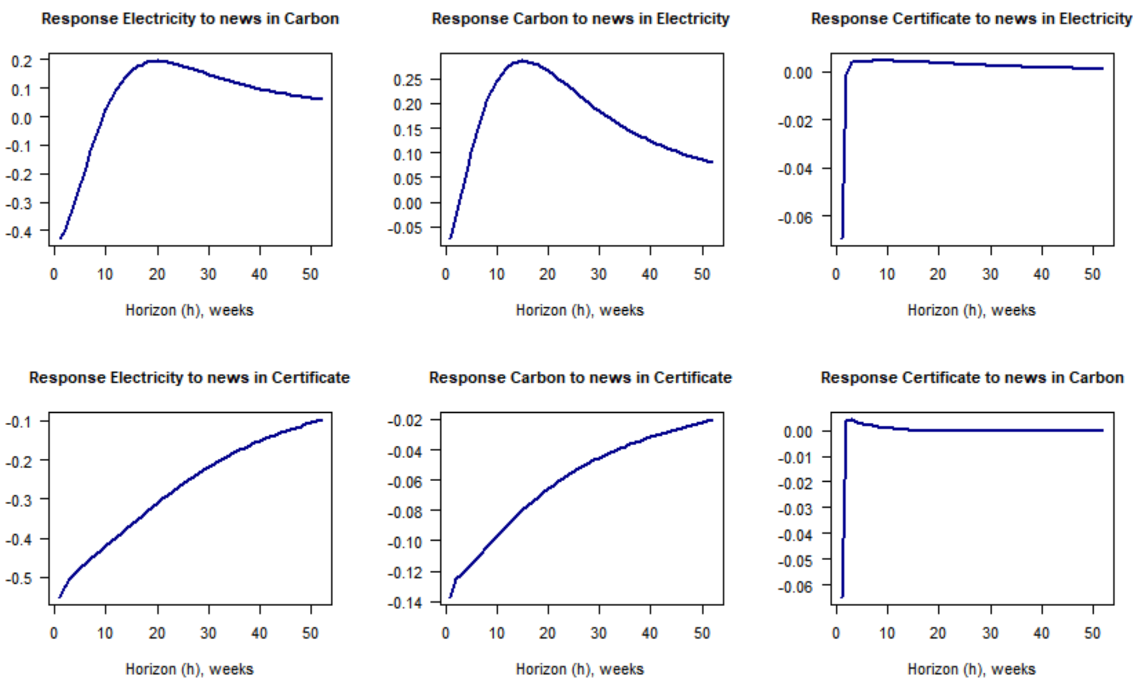

Fig. 5: VIRFs ($p = 0.01$) calculated according to the description in Section 4.3.3 for sample period 2009-2016. The first, second and third columns illustrate the cross-market responses in variance of electricity, carbon and certificate returns, respectively, over a one year horizon.

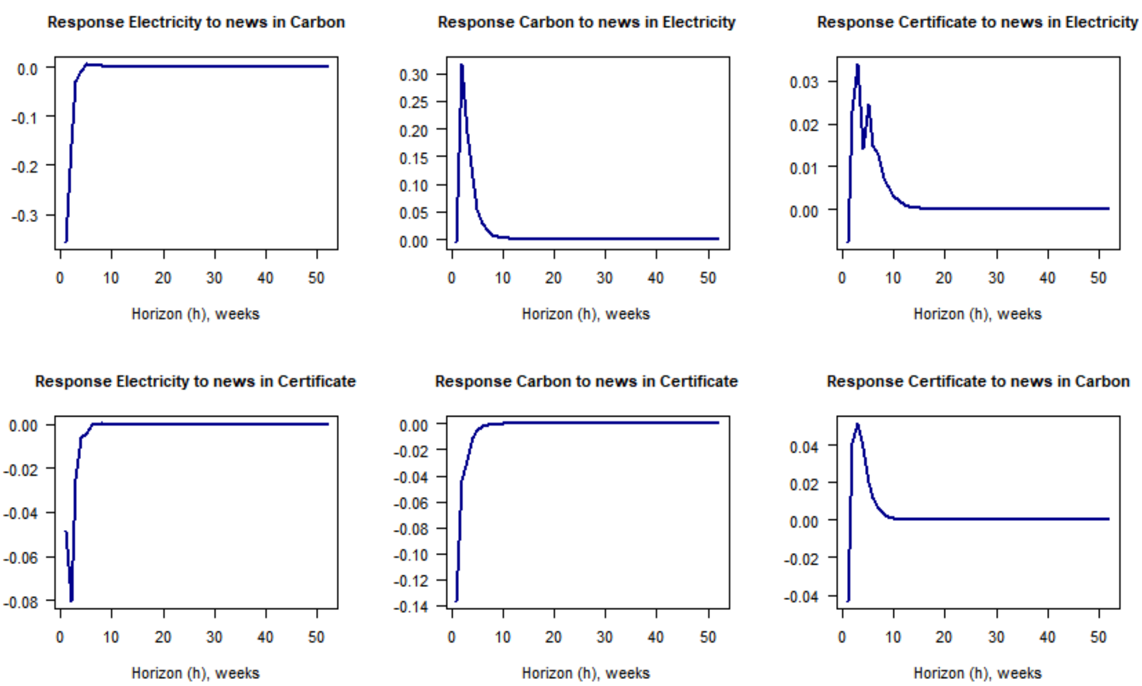

Fig. 6: VIRFs ($p = 0.01$) calculated according to the description in Section 4.3.3 for sample period 2017-2019. The first, second and third columns illustrate the cross-market responses in variance of electricity, carbon and certificate returns, respectively, over a one year horizon.

response in the opposite direction is visible in the same period in this scenario, peaking at around 20% 20 weeks after the shock hits. The VIRFs following a news event in the TGC market remain negative and decaying throughout the sample period. This could be explained by the smaller size of the TGC market compared to the EU ETS and the Nordic power market - a feature not fully captured in the theoretical literature (Schusser and Jaraitė, 2018).

One key finding of these impulse response analyses is the fact that increased uncertainty in electricity prices leads to a rise in expected future uncertainty over both carbon and certificate prices, at least when a large shock is introduced. Comprised with the positive response in expected certificate volatility to increased volatility in carbon prices, this signals an existence of a direct as well as an indirect (disrupting) interaction between TGC and carbon emissions markets, in line with the reasoning in Rathmann (2007).

7 Summary and conclusions

This study investigates volatility spillover between the Nordic power market (Nord Pool), the EU Emissions Trading System (EU ETS) and the Swedish-Norwegian Tradable Green Certificate (TGC) market. ETS and TGC schemes are market-based energy policies designed to mitigate carbon emissions and stimulate investments in sustainable energy projects. Because they both affect the costs and revenues of power generation, they are connected to the wholesale electricity market. Furthermore, theoretical studies have suggested that the combination of ETS and TGC schemes may create undesirable interactions that disrupt the price formation in these markets. Meanwhile, the few existing empirical studies that examine interdependices between such markets are limited to focus on co-movements in the mean of the commodity prices. This study contributes to the research field by investigating co-movements in their second moments.

For that purpose, a VAR-BEKK model is estimated, allowing for rich interactions between the markets. To quantify the spillover in volatility between the commodities, a Volatility Impulse Response Function (VIRF) analysis is conducted. By then a value-at-risk estimation is employed to analyse how, on average, independent news events, such as policy announcements, appearing in one of the markets is expected to propagate through the multivariate system. After identifying a structural break in the certificate price series in 2017, the empirical analysis is divided into two subperiods. The first ranging from the first week of February 2009 until the last week of 2017, and the second ranging from the first week of 2017 until the last week of 2019.

The empirical results show evidence of spillover effects between all three markets. The strongest and most persistent transmission in volatility occurs between the prices of wholesale electricity and carbon emission allowances, although only a large shock to carbon prices generates a positive response in electricity volatility. No volatility transmission between certificate and electricity prices is identified in the first subperiod but some evidence of bidirectional spillover in the second subperiod can be inferred from the BEKK estimates. Accordingly, the VIRF shows a small, yet positive, impact on certificate volatility in response to a large shock in electricity prices in this period. Similarly and noteworthy, a small positive response in certificate volatility to a shock in carbon prices is identified in the second subperiod and is of meaningful magnitude when the shock is large but less frequently occurring.

It is believed that these differences between the periods in part can be explained by the characteristics of the Swedish and Norwegian energy mixes. Electricity generation in these countries was relatively independent of carbon-based power plants already before the Swedish launch of the TGC market in 2003, suggesting that the TGC scheme had a small initial impact on RES-E generation and hence on the price formation at Nord Pool. Meanwhile, the continued expansion of RES-E technologies in the Nordic power system along with highly volatile certificate prices in recent years may explain an increasing second-moment interdependence between the TGC and the power markets, and in turn between the TGC market and the EU-ETS.

One important implication of these results is the following. The fact that only very large, but less probable, price shocks in the power and the carbon markets are found to notably increase certificate price volatility could be considered as good news when it comes to designing functioning climate policy portfolios. However, the same outcome may not emerge if a TGC scheme in combination of a carbon emissions market is introduced in countries with an energy mix more heavily dependent on carbon-based power generation. In that case the transmission in volatility could be more substantial. Thus, all in all, this study shows that the prices of these three commodities are connected through their second moments and finds evidence of positive cross-market volatility transmission. Taking these spillovers into account could therefore improve the accuracy of forecasts to agents in the power sector. In addition, as emphasised by Blyth et al. (2009), it is important to consider these interactions when coordinating market-based climate policies in order to minimise the risks of investing in sustainable energy projects.

A number of shortcomings and extensions could be considered in future research to improve this study. Primarily, I find that the statistical programs used for estimating the BEKK models are quite sensitive to the choice of starting values for the optimisations, which may question the stability of the obtained parameters. Hence it could be a good idea to put greater effort into finding appropriate starting parameters.

Taking into account the fat-tails of the data distributions may improve the estimates as well. Extensions could be to also investigate the conditional correlations between the commodity prices for a broader analysis of their co-movements, and to consider energy (fuel) markets that affect profits to power producers. Advancing the methodological approach to incorporate asymmetric effect in conditional volatility would be an interesting extension as well. It should further be noticed that the second analysed subperiod consists of a small sample of time series observations. As more data becomes available, further research should be considered for a more comprehensive analysis of how interactions between market-based climate policies evolve over time and during different phases of the schemes.

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Appendix

Table A1: VAR(1) estimates for the conditional means.

Panel A: Sample period 2009-2016					
η_1	-0.001	η_2	-0.001	η_3	-0.002
	(0.007)		(0.003)		(0.001)
ϕ_{11}	-0.018	ϕ_{21}	0.021	ϕ_{31}	-0.001
	(0.049)		(0.022)		(0.008)
ϕ_{12}	0.219***	ϕ_{22}	0.139***	ϕ_{32}	0.016
	(0.112)		(0.049)		(0.019)
ϕ_{13}	-0.045	ϕ_{23}	0.128	ϕ_{33}	0.246***
	(0.286)		(0.126)		(0.048)
Panel B: Sample period 2017-2019					
η_1	-0.001	η_2	0.013***	η_3	-0.004
	(0.008)		(0.005)		(0.007)
ϕ_{11}	-0.072	ϕ_{21}	0.027	ϕ_{31}	-0.068
	(0.081)		(0.054)		(0.072)
ϕ_{12}	0.098	ϕ_{22}	-0.187***	ϕ_{32}	0.030
	(0.119)		(0.079)		(0.106)
ϕ_{13}	0.130	ϕ_{23}	0.053	ϕ_{33}	0.259***
	(0.091)		(0.060)		(0.081)

Notes: Parameter estimates for Eq. (1). $\phi_{i,j}$ is the coefficient for the first lag of commodity j on commodity i for $i, j = 1$ (electricity), 2 (carbon) and 3 (certificate). Standard errors in parenthesis. *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

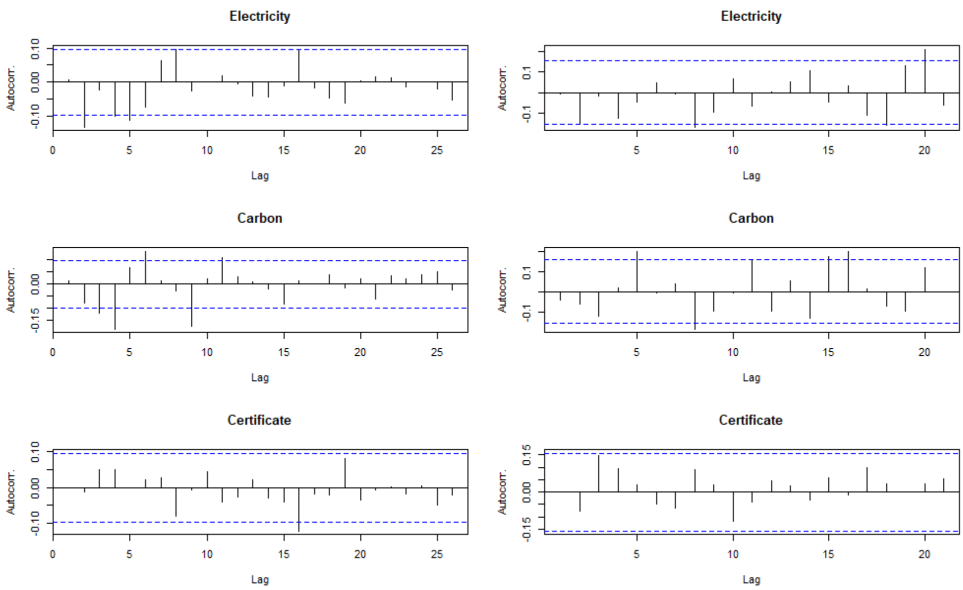

Fig. A1: Autocorrelation in the standardised residuals retrieved from the VAR(1) specifications of Eq. (1). The first and second columns correspond to the first (2009-2016) and second (2017-2019) sample periods, respectively. The dashed blue lines mark the 95% confidence intervals.

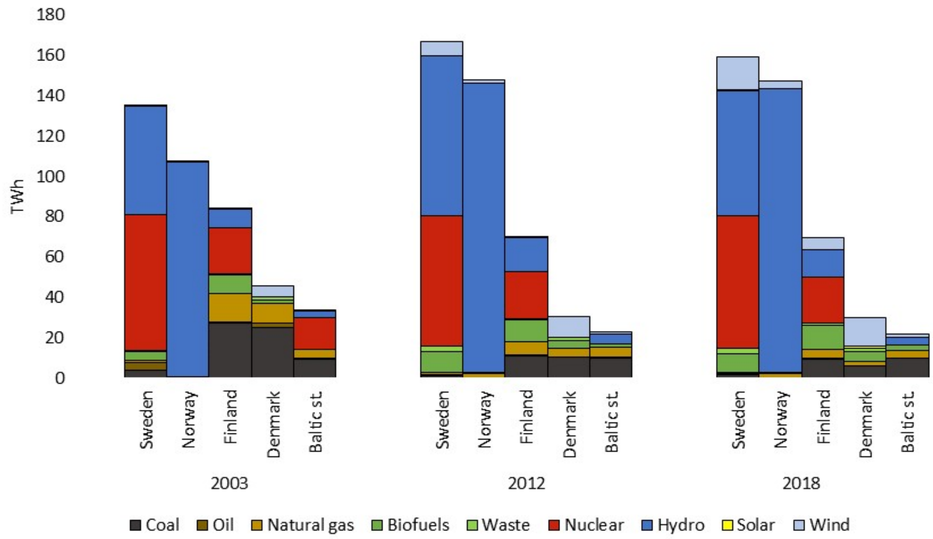

Fig. A2: Electricity production per fuel type in each of the Nordic countries and the Baltic states (Lithuania, Latvia and Estonia). Source: International Energy Agency (`https:iea.org`).