Return spillovers between green energy indexes and financial markets: a first sectoral approach

Capucine Nobletz

2021-24 Document de Travail/ Working Paper

EconomiX - UMR 7235 Bâtiment Maurice Allais
Université Paris Nanterre 200, Avenue de la République
92001 Nanterre Cedex

Site Web : economix.fr
Contact : secreteriat@economix.fr
Twitter : @EconomixU

Return spillovers between green energy indexes and financial markets: a first sectoral approach

Capucine NOBLETZ †

July 14, 2021

Abstract

This paper assesses the interconnectedness between global green energy and sectoral stock indexes. We show that green energy return spillovers need to be monitored. The green energy index has a significant degree of financial openness, and it is tightly interconnected with sectors producing similar goods as materials or industrials. Over time, the green energy return spillovers vary according to global events and economic/financial uncertainties. Spillovers rose during the pandemic crisis, illustrating the "fly to liquidity" mechanism.

Key words: Financial markets, Green energy stocks, Sectoral indexes, Spillovers, Networks.

JEL classification: C32, G15, Q42.

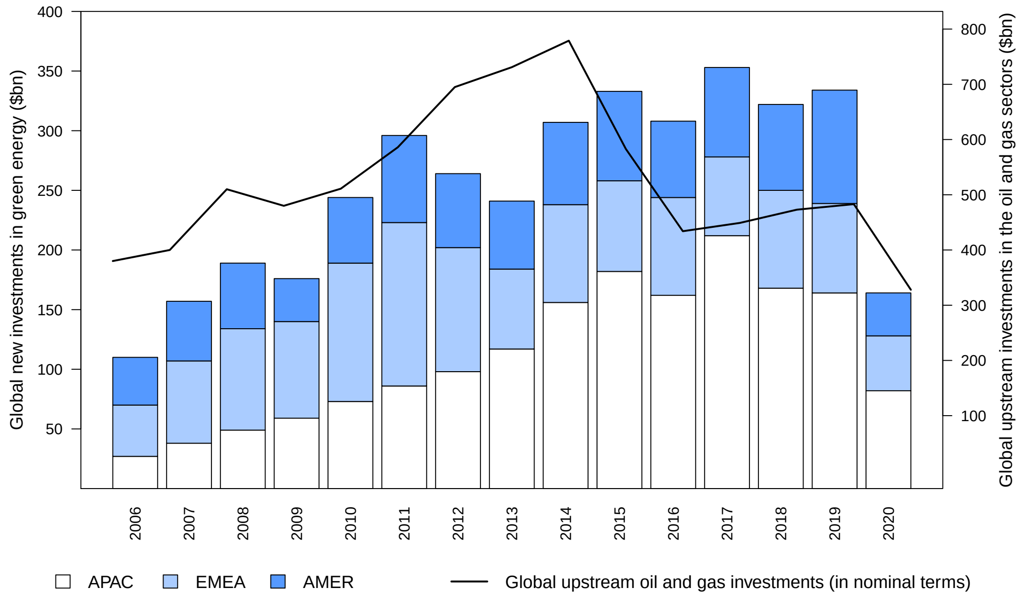
Acknowledgements: The author would like to thank her thesis advisor Valérie Mignon for her availability, advice, and listening. The author would also like to thank Elena Dumitrescu and Gilles de Truchis for reviewing her work and providing comments that significantly improved the article. Finally, the author would like to address special thanks to her office colleagues for their unfailing support.

†EconomiX-CNRS, UPL, Univ Paris Nanterre, CNRS, 92000 Nanterre France.
Emails: capucine.nobletz@gmail.com / cnobletz@parisnanterre.fr

1 Introduction

Since 1950, there has been an intensification of extreme weather and climate phenomena such as rising global temperatures, rising sea levels, or increasing ocean acidification. The Intergovernmental Panel on Climate Change (IPCC, 2014) estimates a 95% probability that human activities are the leading cause, mainly through increased greenhouse gas emissions. Therefore, in December 2015, the Paris agreement is signed; today, 183 out of 197 Parties have ratified it and thus committed to limit the global temperature increase to well below 2 degrees compared to preindustrial levels (UNFCC). Changes in the economic landscape are essential, especially in the energy, industry, or transport sectors. However, the fiscal policies alone, such as carbon taxes or prices, will not be sufficient (Sachs, 2015; Sartzetakis, 2020). Therefore, the financial system has a pivotal role in supporting green investment growth.[1]

Figure 1: Investments in global green energy and upstream oil and gas sectors



Note. APAC: Asia-Pacific region, EMEA: Europe Middle East and Africa region, AMER: North Central and South-America region.
Source. Right axis - World Energy Outlook, IEA (2016; 2020); Left axis - BloombergNEF's Clean Energy Investment Trends report (2020).

As shown in Figure 1, there is strong growth in new green energy investments worldwide relative to growth in the upstream oil and gas sector, declining since the 2014 oil price drop. Stock or bond issues mainly finance these green projects driving by the APAC (Asia-Pacific), EMEA (Europe, Middle East, and Africa), and AMER (North, Central, and South America regions). Nevertheless, the pandemic crisis has generated a fall in global green energy investments (BloombergNEF, 2020).

[1]Green investments can be defined as investments in productive sectors that contribute to improving the economic system's environmental sustainability (Campiglio, 2016).

The expanding demand for green energy assets raises the question of their interconnections with financial markets. Are they immune to external financial shocks? Do they tend to be transmitters or receivers of shocks? Besides, are they more tightly interconnected with specific economic sectors?

This paper addresses this issue by analyzing return spillovers between green energy indexes and financial markets at the aggregated and sectoral levels. We focus on the global market and use the "WilderHill New Energy Global Innovation" index (NEX) and the S&P Global 1200 sectoral indexes over the period from 2006-03-06 (NEX launch date) to 2020-06-19. Our main contribution to the existing literature is that we pay particular attention to the sectoral dimension. Indeed, to the best of our knowledge, our paper is the first to propose a sectoral level analysis, which contributes to a better understanding of the dynamics of green energy stock indexes.

Our analysis is particularly relevant for public authorities and financial investors. Indeed, it is helpful for public authorities as it allows them to understand better the shock transmission mechanisms between green energy and economic sector returns. In other words, it emphasizes how a policy promoting the development of green energy products and thus leading to higher returns could impact those of other economic sectors. Besides, this analysis could also better lighten how a low-carbon policy leading to disruptions in some economic sectors and therefore on their asset prices/returns could translate toward green energy financial returns.[2] Moreover, this study could help financial investors with hedging perspectives. Suppose investors want to reduce the return risks of green financial products. In that case, they might be interested in investing in economic sectors where the interconnection with the green financial indexes is the lowest.

As for methodological considerations, and given the conduct of a comprehensive analysis, we first verify that the green energy index and the global financial index contribute to the other's forecast by implementing Granger causality tests. Second, we model the interconnection between green and sectoral stock indexes by estimating a VAR model and then applying the methodology of Diebold and Yilmaz (2014). We perform the generalized forecast error variance decomposition of Koop et al. (1996) and construct spillover indexes. Confidence intervals of the estimated coefficients are computed by the fixed-effect wild bootstrap as this resampling method deals with conditional heteroskedasticity. Finally, we extend this investigation by analyzing the spillover indexes' time variation with rolling window methods.

The main results are the following. First, the green energy index has a significant degree of financial openness, and it receives more shocks than it transmits to sectoral stock markets.

[2] There is a wide range of green macroprudential policies (for a survey, see Orazio and Popoyan, 2019). For example, we have credit policies aiming to restrict banks' lending activities towards polluting activities and sectors.

Second, the green energy index is more interconnected with the material and industrial sectors. We explain this result by (i) the financial openness of these sectors and (ii) the similarity of goods produced between the green and the material/industrial sectors. Third, green energy return spillovers vary over time; they follow economic and financial uncertainties.

The paper is organized as follows. Section 2 provides a brief overview of the existing literature. Sections 3 and 4 present the data and the methodology used, respectively. Section 5 outlines the empirical results. Section 6 is devoted to the robustness tests, and Section 7 sets out the main conclusions.

2 Literature review

2.1 Green asset definition

Before reviewing the literature on interconnections between green energy and financial indexes, we need to understand the green stock index characteristics. On this last point, the literature is scarce.

A green stock is a company share whose main activity is not "harmful" to the environment. Defining what is not "harmful" to the environment is far from simple, as there is no consensus on what is "green" or not. The "green" attribute depends on the selection method used. With the "best-in-class" approach, we select the "best" companies in each sector, while with the exclusion approach, we exclude companies that do not meet specific socio-environmental criteria (e.g., armament, nuclear, etc.)(AMF). Moreover, greenness measurement depends on the criteria used: should we use qualitative or quantitative criteria? This definition also varies between countries and their different government policies.

Nevertheless, the literature generally defines activities in renewable energy, wastewater management, or energy efficiency as "green". The nuclear energy and hydropower sectors are more controversial, and the biofuels or shale gas drive consensus shifts (Inderst et al., 2012).

As a result, the lack of clarity around green assets makes us wonder why they are so popular. Inderst et al. (2012) highlight several reasons for investing in green assets (stocks, bonds, etc.): (i) financial motivations (return, risk, and portfolio diversification criteria), (ii) extra-financial motivations (ecological, scientific, ethical, etc.), (iii) reputational motivations (reputation of the investor or company, political pressures, and marketing tools) or (iv) compliance and fiduciary obligations (national laws and regulations, international conventions, etc.).

2.2 Green energy indexes & financial markets

To our best knowledge, we are the first to model return spillovers between green energy and sectoral stock indexes. Most studies analyzing relationships with green energy indexes focus on interconnections between these indexes, crude oil (or energy indexes), and high-tech indexes.

Overall, the literature highlights that (i) high-tech stock indexes impact strongly and positively green energy indexes, while (ii) energy sectors play minor roles.

On the first point, the literature puts forward several hypotheses to explain this relationship: (i) the returns of high-tech stocks drive those of green energy through a "price signal" (Henriques and Sadorsky, 2008; Kumar et al., 2012; Sadorsky, 2012; Managi and Okimoto, 2013; Inchauspe et al., 2015; Ferrer et al., 2018), and (ii) these two assets *"compete for the same inputs,"* such as highly skilled engineers and researchers, semiconductors, or thermoelectric materials. The green index composition corroborates the latter assertion; there is a high concentration of technology companies in green energy indexes (Nobletz, 2021).

On the second point, substitution effects between the green and the energy sectors appear to be weak (Henriques and Sadorsky, 2008): an increase (or decrease) in oil prices has small repercussions on the green energy demand and, consequently, on their prices. Nevertheless, there is no clear consensus about this relationship; some authors find a positive relationship (Kumar et al., 2012; Managi and Okimoto, 2013), while others not (Ferrer et al., 2018). Some researchers answer this issue by showing that this relationship is time-varying (Inchauspe et al., 2015; Reboredo, 2015; Reboredo et al., 2017; Ahmad and Rais, 2018). According to Reboredo et al. (2017), this dependence is weak in the short term but strengthens in the long term.

Moreover, the literature identifies strong connectivity between green energy indexes and financial markets (Henriques and Sadorsky, 2008; Kumar et al., 2012; Managi and Okimoto, 2013; Inchauspe et al., 2015; Bondia et al., 2016; Ferrer et al., 2018). As shown by Henriques and Sadorsky (2008), Kumar et al. (2012), Managi and Okimoto (2013), and Bondia et al. (2016), there is a positive relationship between interest rates (measured with the three-month US Treasury Bill) and green energy indexes. Inchauspe et al. (2015) underline that the MSCI World Index and the global green energy index are highly correlated. Ferrer et al. (2018) show that renewable energy indexes are net transmitters of return and volatility spillovers on the US financial market.

Finally, we observe a panel of methods to analyze this issue. Henriques and Sadorsky (2008), and Kumar et al. (2012) estimate a vector autoregressive model (VAR) to compute generalized impulse response functions (GIRF) and Granger causality tests. Others use Diebold and Yilmaz (2012, 2014) methodology (Ahmad, 2017; Ahmad and Rais, 2018; Pham, 2019) or its extension introduced by Baruník and Křehlík (2018) in the frequency domain (Ferrer et al., 2018). Several papers also employ a model belonging to the ARCH-GARCH family (Broadstock et al., 2012; Sadorsky, 2012; Wen et al., 2014; Ahmad, 2017; Ahmad and Rais, 2018; Dutta et al., 2018; Pham, 2019; Dutta et al., 2020). Some use copula methods (Reboredo, 2015; Reboredo and Ugolini, 2018; Elie et al., 2019). At last, Managi and Okimoto (2013) and Inchauspe et al. (2015) employ, respectively, the state-space multi-factor asset pricing model with time-varying coefficients and Markov-switching vector autoregressive models. Reboredo et al. (2017) rely on continuous and discrete wavelets.

In the next section, we detail the data selection process and present descriptive statistics.

3 Data

3.1 Data selection process

The main challenge we face is to select green and sectoral indexes for which we have access to their compositions each year.[3] Indeed, we want to verify that no or few firms simultaneously make up the green and the financial indexes, as the risk is to create a dependency between them artificially.

For the green energy index, we select the "WilderHill New Energy Global Innovation Index" (NEX), which is composed of companies *"whose innovative technologies focus on generation and use of cleaner energy, conservation, efficiency, and the advancement of renewable energy [...]"* (NEX Rule Book, 2020). Indeed, it provides an overall representation of the environmental sectors, and an exclusionary approach is applied to select companies. It has a long history and serves as a benchmark for investors and academics. Its composition is also accessible for each year.

We find that, from 2006 to 2020, the NEX index composition is highly volatile. This index is roughly composed of 100 global companies, but 309 companies have composed it in all years. This result can be explained both by the environmental market's youthfulness and the NEX's eligibility criteria. In this market, companies are more likely to go bankrupt, to be absorbed by larger companies, or not to be able to get sufficient capitalization from one year to another. Moreover, the NEX composition tracks changes in the green energy market: there is a growing role in the index of Pacific-Asian companies and firms in the wind and solar sectors in recent years. Finally, the companies' weights are limited in the index constitution; it is unlikely that few firms draw market variations from the index.

For the sectoral stock indexes, first, we have to select between the production-oriented classification and the market-oriented classification. We select the market-oriented classification as it

[3]Following a consequent data treatment, the coming paragraphs are the synthesis of Nobletz (2021); we refer the readers to this paper for more information.

is followed by the financial community (i.e., for stock screening or sector identification)(Phillips and Ormsby, 2016). Second, we have to discriminate between the two main classifications belonging to this family: the GICS (Global Industry Classification Standard, 1997) and the ICB (Industry Classification Benchmark, 2001). These classifications allow a better representation of the sectoral concentration (Hrazdil and Zhang, 2012) and perform to explain stock market return comovements (Bhojraj et al., 2003). The GICS is produced by the MSCI and the Standard & Poor's (S&P), while the Dow Jones and the FTSE produce the ICB. As our study focuses on the global level, we select the GICS classification to use the S&P Global 1200 sectoral indexes. There are eleven sectors: Communication Services, Consumer Discretionary, Consumer Staples, Energy, Financials, Health Care, Industrials, Information Technology, Materials, Real Estate, and Utilities.[4] Third, we retrieve the indexes' compositions for all years and check the GICS 2018 restructuring impact on the sectoral indexes. We find that 33 companies over 1200 have changed sectors, which is negligible.

Finally, we find that 22 companies are both in the NEX and the S&P Global 1200. Twenty-two companies are negligible for the S&P Global 1200, but it is more substantial for the NEX. On this latter point, ten companies make up the index for less than two years, and only three make up the index for all years. Therefore, these results are positive. The risk of creating multicollinearity between indexes is negligible.

3.2 Selected data

As emphasized in the previous section, we select the NEX and the S&P Global 1200 Communication Services, Consumer Discretionary, Consumer Staples, Energy, Financials, Health Care, Industrials, Information Technology, Materials, Real Estate, and Utilities.[5] The data comes from Datastream, and the period runs from 2006-03-06 (NEX launch date) to 2020-06-19 daily. All the variables are in the first logarithmic difference (Figure A) to deal with non-stationarity issues.[6]

Figure 2 shows that the NEX and the S&P Global 1200 sectoral indexes (in logarithm) co-move strongly and positively. First, the indexes are characterized by a positive trend even though they have experienced significant declines in crisis times (e.g., 2008 and 2020). During the Covid-19 crisis, we observe the market crash and that nowadays, index prices have returned

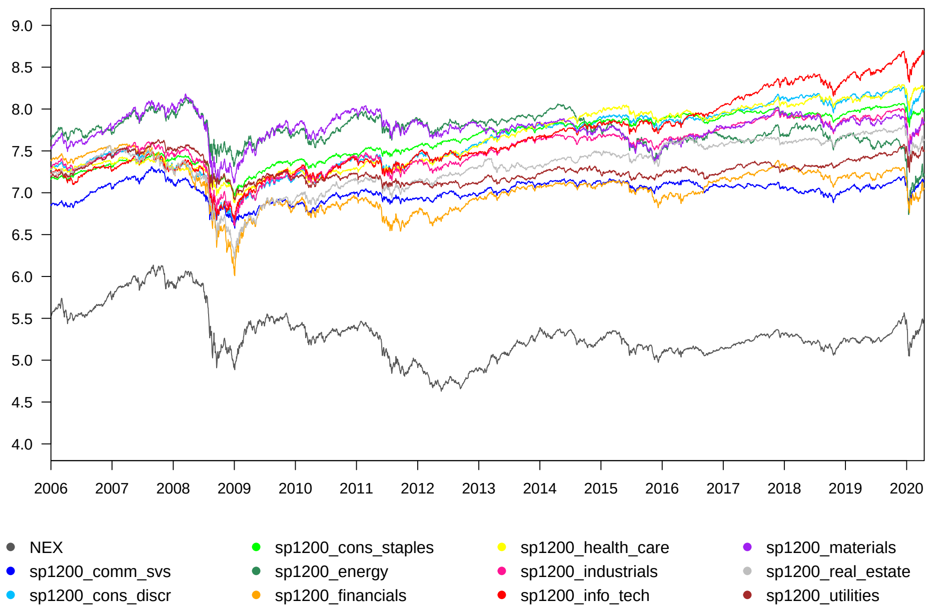
[4]We concentrate this analysis on the sectors and not on the 24 industry groups, 69 industries, or 158 sub-industries as the risk of going down to a more advanced level is to drowning in information.

[5]We do not include the VIX (Figure B) in our model as it has statistical properties that are incompatible with returns (high persistence), which leads to inconsistent estimates (Sun, 2004). Finally, it would have been relevant to include the public environmental expenditures in the model, but these data are unfortunately not available at the global level with a daily frequency.

[6]According to Augmented Dicker-Fuller – ADF (Dickey and Fuller, 1981), Kwiatkowski-Phillips-Schmidt-Shin test – KPSS (Kwiatkowski et al., 1992), and Philips-Perron – PP (Phillips and Perron, 1988) tests, all series in logarithm are non-stationary at conventional levels. In the first log difference, all tests conclude that all series are stationary at 5% (Table A).

to their pre-pandemic level.[7] Second, the NEX is more volatile than the S&P Global 1200 sectoral indexes. Investors are more likely to withdraw their green financial investments during crisis because they are looking for safer assets ("fly to liquidity" e.g., 10-year sovereign bonds), while in expansion periods, they are more inclined to take risks. Besides, ethically, agents are more willing to finance the environmental transition in expansion periods, while financial concerns prevail in crisis times. The green index more volatile constitution can also explain this phenomenon (Section 3.1).

Figure 2: The NEX and the S&P Global 1200 sectoral indexes (log)



Source. Datastream

Finally, we perform Granger causality tests (Table B) to check whether there is a causal relationship between the aggregated variables before going down to a sectoral level. We identify a bi-directional Granger causality between the S&P Global 1200 and the NEX at 5%. There is a feedback effect: the S&P Global 1200 returns contribute to the forecasts of the NEX returns (and conversely).

Since these two variables contribute to each other's prediction, it is relevant to perform a network analysis of interconnections at a more advanced level. This analysis no longer focuses on the VAR coefficients but on the VAR forecast errors' variance decomposition. We explain this methodology in detail in the following section.

[7]However, it is still too early to know the magnitude of the pandemic's effect on the financial markets.

4 Methodology

4.1 Connectedness measures

Different connectedness measures exist, such as the Marginal Expected Shortfall (MES) (Acharya et al., 2010, 2012), the CoVaR (Adrian and Brunnermeier, 2011), the pairwise Granger causality (Billio et al., 2012), or the equi-correlation (Engle and Kelly, 2012). In a series of papers (2009, 2012, 2014), Diebold and Yilmaz use forecast error variance decomposition of VAR(p) model to compute spillover indexes; we follow this methodology. Indeed, the Marginal Expected Shortfall and Expected Capital Shortfall approaches analyze firm sensitivity to extreme market risks (financial markets → firm) while the CoVaR approach measures the firm systemic nature to financial markets (firm → financial markets). Diebold and Yilmaz spillover indexes mix these two approaches; the directional spillover indexes allow measuring whether an asset is more receiver or transmitter of shocks in the system. Besides, this methodology provides greater granularity, as we can analyze pairwise spillovers between all system assets (Diebold and Yilmaz, 2014).

Diebold and Yilmaz have refined their method over time. In the 2009 paper, the Cholesky factorization achieves orthogonality. Hence, the variance decomposition depends on the order of the variables. We could compute the VAR models corresponding to all possible permutations of variables (Faust, 1998), but this solution is too time-consuming. Moreover, it would be hazardous to justify a specific order in the variables as we have established bidirectional causality between the S&P Global 1200 and the NEX. In 2012 and 2014 papers, they address this issue by implementing the generalized VAR framework of Koop et al. (1996); this approach allows innovations (shocks) to be correlated but takes them into account appropriately using the historically observed error distribution.

Therefore, we use the methodology of Diebold and Yilmaz (2014) and construct the confidence intervals/distributions of the variance decomposition matrix using the fixed-effect wild bootstrap. This residual resampling method accounts for conditional heteroskedasticity of unknown form leading to valid inference (Gonçalves and Kilian, 2004).[8]

4.2 Spillover indexes

To compute spillover indexes, we apply the Diebold and Yilmaz (2014) methodology based on the generalized VAR variance decomposition of Koop et al. (1996).

[8]The bootstrapping residuals $\hat{\varepsilon}_t^*$ take the following form: $\hat{\varepsilon}_t^* = \hat{\varepsilon}_t.\eta_t$ where $\hat{\varepsilon}_t = \hat{\Phi}(L)y_t$ are the estimated residuals of the OLS model and η_t is an i.i.d sequence with mean zero and variance one (Gonçalves and Kilian, 2004).

First, consider a covariance stationary N-variable VAR(p):

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

Where ε is a N-vector of identically and independently distributed (i.i.d.) errors with zero mean and covariance matrix, $\sum$. We transform the model into its moving average representation:

$$x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i} \tag{2}$$

where A_i is a $N * N$ coefficient matrix and has the following form: $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \cdots + \Phi_p A_{i-p}$. A_0 is a $N * N$ identify matrix with $A_i = 0$ for $i < 0$.

Second, we calculate the generalized h-step-ahead forecast error variance decomposition, $\theta_{ij}^g(H)$:

$$\theta_{ij}^g(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \sum e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \sum e_i)} \tag{3}$$

With $\sum$, the error vector variance matrix; σ_{jj}, the standard deviation of the error term for the j^{th} equation, and e_i the selection vector, a vector which takes the value of one at the i^{th} element and zero otherwise.

As there is no error orthogonalization, the sum of each variable's forecast error variances (the sum of the error variances by row) is not necessarily equal to one: $\sum_{j=1}^{N} \theta_{ij}^g(H) \neq 1$. Therefore, we normalize each variance of the matrix by the row sum, equal to the number of variables, N.

$$\tilde{\theta}_{ij}^g(H) = \frac{\theta_{jj}^g(H)}{\sum_{n}^{j=1} \theta_{ij}^g(H)} \longrightarrow \sum_{i,j=1}^{N} \tilde{\theta}_{ij}^g(H) = N \tag{4}$$

Third, we measure the total spillover index, and as the covariance matrix is independent of the variable ordering, we also compute the directional and the net spillovers.

The Total Spillover Index (TSI) measures the system's overall connectedness:

$$S^g(H) = \frac{\sum_{i,j=1, i\neq j}^{N} \tilde{\theta}_{ij}^g(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^g(H)} * 100 = \frac{\sum_{i,j=1, i\neq j}^{N} \tilde{\theta}_{ij}^g(H)}{N} * 100 \tag{5}$$

The directional spillovers are spillovers transmitted by a variable <u>to</u> all others (to) and spillovers received by a variable <u>from</u> all others (from).

$$S_{i.}^g(H) = \frac{\sum_{j=1, j\neq i}^{N} \tilde{\theta}_{ij}^g(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^g(H)} * 100 = \frac{\sum_{j=1, j\neq i}^{N} \tilde{\theta}_{ij}^g(H)}{N} * 100 \tag{6}$$

$$S^g_{.i}(H) = \frac{\sum_{j=1,j\neq i}^{N} \tilde{\theta}^g_{ji}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}^g_{ji}(H)} * 100 = \frac{\sum_{j=1,j\neq i}^{N} \tilde{\theta}^g_{ji}(H)}{N} * 100 \tag{7}$$

The net spillovers (net) are the difference between the "to" and "from" indexes. Therefore, if $S^g_i(H) > 0$, the variable is a net transmitter of shocks, and if $S^g_i(H) < 0$ it is a net receiver of shocks.

$$S^g_i(H) = S^g_{.i}(H) - S^g_{i.}(H) \tag{8}$$

The net pairwise spillover between the variables x_i and x_j, is the difference between the pairwise spillover of i to j ($x_i \rightarrow x_j$), and the pairwise spillover of j to i ($x_j \rightarrow x_i$).

$$S^g_{ij}(H) = [\frac{\tilde{\theta}^g_{ji}(H)}{\sum_{i,k=1}^{N} \tilde{\theta}^g_{ik}(H)} - \frac{\tilde{\theta}^g_{ij}(H)}{\sum_{j,k=1}^{N} \tilde{\theta}^g_{jk}(H)}] * 100 \tag{9}$$

$$S^g_{ij}(H) = [\frac{\tilde{\theta}^g_{ji}(H) - \tilde{\theta}^g_{ij}(H)}{N}] * 100$$

Finally, to analyze these spillover indexes in a static setting, we compute the spillover table (Table 1):

Table 1: Spillover table

	x_1	x_2	x_3	...	x_N	from
x_1	p_{11}	p_{12}	p_{13}	...	p_{1N}	$\sum_{j=1,j\neq 1}^{N} p_{1j}$
x_2	p_{21}	p_{22}	p_{23}	...	p_{2N}	$\sum_{j=1,j\neq 2}^{N} p_{2j}$
x_3	p_{31}	p_{32}	p_{33}	...	p_{3N}	$\sum_{j=1,j\neq 3}^{N} p_{3j}$
...	...	...	...	...	...	...
x_N	p_{N1}	p_{N2}	p_{N3}	...	p_{NN}	$\sum_{j=1,j\neq N}^{N} p_{Nj}$
to	$\sum_{i=1,i\neq 1}^{N} p_{i1}$	$\sum_{i=1,i\neq 2}^{N} p_{i2}$	$\sum_{i=1,i\neq 3}^{N} p_{i3}$	...	$\sum_{i=1,i\neq N}^{N} p_{iN}$	$TSI = \frac{1}{N} * \sum_{i,j=1,i\neq j}^{N} p_{ij}$

The "own-variance shares" are the matrix's diagonal elements (without the TSI); p_{ii} is the share of forecast error variance that x_i transmits to itself. The pairwise spillovers are, therefore, elements of the off-diagonal matrix (without "to" and "from" indexes); p_{ij} is the share of variance that x_i received from x_j. Besides, the from (to) indexes are the row (column) sum for each variable minus its own-variance share. Finally, the TSI is the sum of the pairwise spillovers divided by N (Diebold and Yilmaz, 2012, 2014).

5 Results

This section analyzes the spillover table in a static sample, allowing us to capture the average behaviors. Then, we push the analysis by looking at how the spillover indexes vary over time.

5.1 Full-sample static analysis

We run the 12-VAR(1) model, transform it into its moving average form, and compute the 10-step-ahead forecast error variance decomposition.[9] We do inference on the estimated parameters using the bootstrap adapted to the residuals' conditional heteroscedasticity; the bootstrap number is 5000. Hence, we provide Efron percentile confidence intervals for the estimated parameters of the variance decomposition matrix (Table C) and plot the spillover indexes' distributions (Figures E, F).[10] All estimated coefficients fall within their respective confidence intervals.

To ease the reading of the spillover table (Table C), we compute a network graph of pairwise spillovers (Figure 3) using the ForceAtlas2 algorithm of Jacomy et al. (2014).[11] Nodes' size denotes the assets' interconnectedness degree: the larger the node, the more the asset is connected in the system. Nodes' location and links indicate the "to" and "from" pairwise spillovers: their sizes are proportional to the percentage variance of the error predictions they transmit or receive from other assets. The nodes' color indicates the "to-degree": the darker the color, the more the asset transmits shocks in the system.

[9] In this model, we choose the SIC over AIC criterion – one lag versus six – to avoid over-parameterization and allow for greater parsimony. We also emphasize the VAR model stability. Finally, the h-forecast horizon is explained as follows: *"in risk management contexts, one might focus on H values consistent with risk measurement considerations. H = 10, for example, would cohere with the 10-day value at risk (VaR) required under the Basel accord"*(Diebold and Yilmaz, 2014). Still, the model is robust to the chosen forecast horizon with h ranging from 5 to 15 days – results on request.

[10] The Efron percentile confidence intervals are the quantiles of the distributions at 2.5% and 97.5%.

[11] The ForceAtlas2 algorithm of Jacomy et al. (2014) is a "*force-direct layout. [...] It simulated a physical system in order to spatialize a network. Nodes repulse each other like charged particles, while edge attracts their nodes, like springs.*"

Figure 3: Network graph

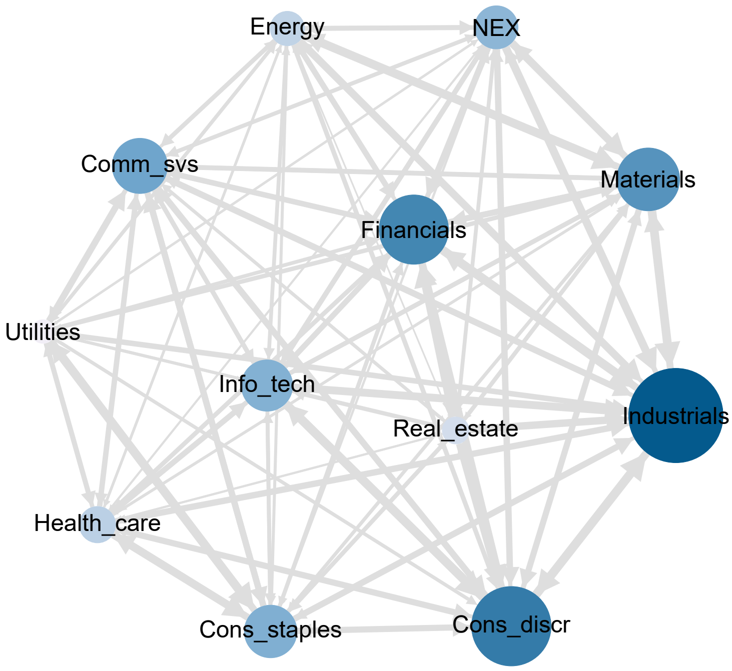
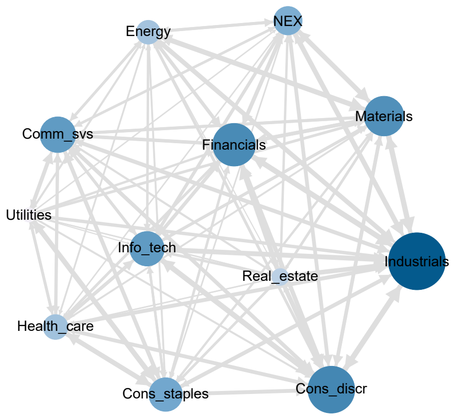
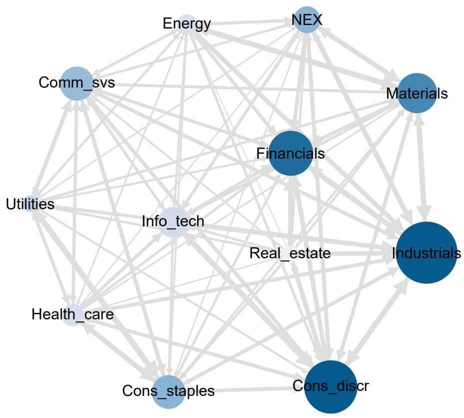


Figure 4: Efron percentile confidence intervals



(a) 2.5%



(b) 97.5%

Note. Networks have been computed with Gephi software. The Efron percentile confidence intervals are the quantiles of the 2.5% and 97.5% distributions. The nodes' position between networks can change slightly; there is no single representation of the system as it depends on the initial state. Nevertheless, each node's location depends on the others; thus, the valid visual representation of the structure is not affected.

First, we underline an expected and observed result in the financial literature: stock markets are strongly interconnected (Diebold and Yilmaz, 2015). According to the TSI, spillovers between variables explain 86.51% of the variance in forecast errors.

Second, the most interconnected financial indexes are the industrial, consumer discretionary, and financial sectors, while the less interconnected are the utility, real estate, health care and energy sectors.[12] These results are not surprising. Nobletz (2021) shows that the leading sectors in the S&P Global 1200 composition are the industrial, financial, and consumer discretionary sectors, while the utility, real estate, and energy sectors are less preponderant. If we approximate the index composition as a reliable representation of global sector concentration, the larger the sector, the more interconnected it is.

Third, our green energy index (NEX) is in an intermediate position. It has a significant degree of financial openness (approximated by the own-variance share), but on average, it receives more shocks than it transmits to others; it is a net receiver of shocks (Figure C). The strong demand for green assets and its volatility explain this result (see Section 3.2).

Fourth, the NEX is more interconnected with the material and industrial sectors. We explain this result in two ways. First, the sectors' financial openness plays a key role, as these two sectors are among the most interconnected; the more financially open firms are, the more they are likely to receive or transmit shocks. Second, the similarity of goods produced between the green energy and the material, industrial sectors could explain this result. For instance, the wind sector includes components for wind turbines and turbine manufacturers. The solar sector includes companies producing technologies capturing sun energy with photovoltaic (PV) materials or solar thermal technologies (concentrators, Stirling engines, etc.). Besides, the NEX is less interconnected with the health care, utility and, consumer staple sectors.

Finally, interconnections are weaker between the green and energy sectors, highlighting that substitution effects are not the key driver. This result is in line with the literature (Henriques and Sadorsky, 2008).

In the next subsection, we deepen this analysis by computing the spillover indexes in a time-varying way.

5.2 Dynamic analysis

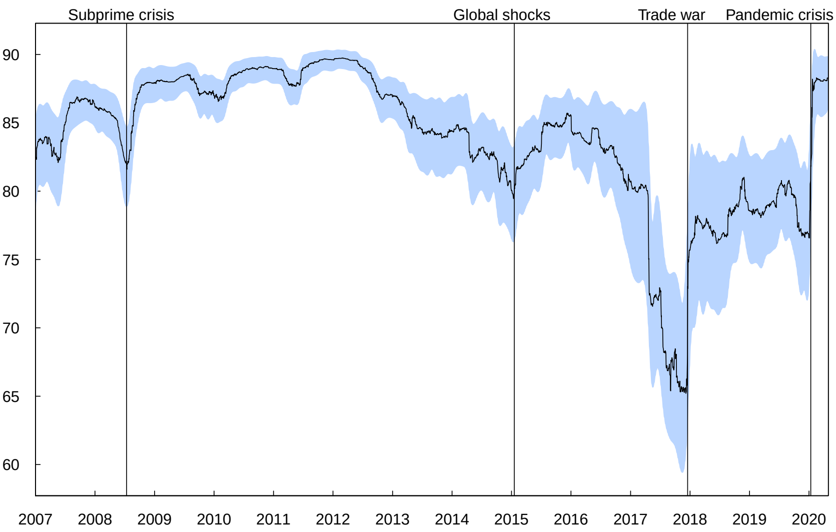
We run rolling windows on the model with a 250-day width (a business year) to analyze the spillover indexes variations. The primary advantage of this method is its ease of implementation and the application of a consistent framework (Diebold and Yilmaz, 2014). We also perform 200 wild bootstraps to construct confidence intervals for the dynamic spillover indexes.[13]

[12] Even if these sectors are less interconnected, their interconnection degree in absolute term remains high. For example, only 14.4% of the forecast error variance is explained by an "itself" shock for the energy sector.

[13] We are not able to run more than 200 bootstraps as we face computational limitations.

5.2.1 Dynamic analysis of the global connectedness

Figure 5: TSI over time



Note. This figure depicts the variations in the Total Spillover Index, estimated with 250-day width rolling windows. We construct Efron percentile confidence intervals with 200 fixed-effect wild bootstraps. Smoothing splines are also applied to these intervals to improve their graphical readability. For more details on the smoothing method, see Green and Silverman (1994).

As shown in Figure 5, there are substantial variations in overall system connectivity. Global interconnectedness follows the level of worldwide uncertainty; it rises in times of global economic or political shocks and falls in times of lull. Candelon et al. (2020) support these findings by matching the Diebold and Yilmaz (2009) methodology with a non-linear effect – threshold VAR. In the following paragraphs, we propose a reading of this graph by analyzing, in a non-exhaustive way, the events that may have caused these variations.

First, we observe an increase in system connectivity around 2008, 2015, 2018, and 2020. In 2008, the global financial crisis occurred, which led to significant disruptions in the financial markets. Numerous shocks also hit the years between 2015 and 2016. In 2015, we had the end of the Swiss franc's peg to the euro, the Chinese economic crisis, the Greek bankruptcy, and the easing of monetary policies worldwide, combined with the rise in federal funds rates. Add to this the terrorist attacks and the refugees' crisis. In 2016, China's stock market crashed, OPEC announced cuts in oil production, Donald Trump became President of the United States, and Brexit was announced. Anxiety rose again in 2018-2019 with the trade war between China and the United States or the tensions over the nuclear negotiations between South Korea and the United States. Finally, in 2020, the pandemic crisis provoked the Great Lockdown and exacerbated the already high uncertainty (Mignon, 2020). The crash of the financial markets then took place, aggravated by a drastic drop in oil prices.

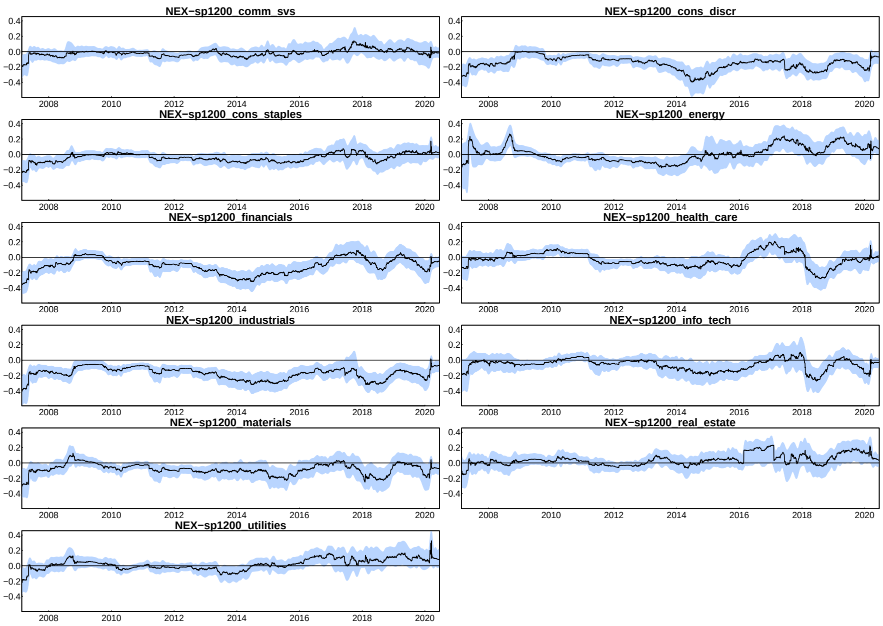
Second, this figure highlights a sharp decline in financial interconnectedness in 2017. This year was indeed characterized by low uncertainty, e.g., the VIX nearly hit its floor value (Figure B). The upholding growth, the rising interest rates, or the flourishing year for the financial markets could explain this finding.

5.2.2 Dynamic analysis of the NEX pairwise spillovers

Figure 6 displays the NEX pairwise spillover indexes and highlights several results. First, on average, the NEX is a net receiver of shocks from all economic sectors. The NEX pairwise indexes are graphically below zero ($net_{NEX} < 0$); thus, they receive more shocks than they transmit to others.

Second, NEX return spillovers vary over time and appear to follow major shocks and events. For instance, it rose in 2007 when the global demand, the public subsidies for environmental sectors, and oil prices were high. It rose again during the pandemic crisis, which could highlight the "fly to liquidity" mechanism.

Figure 6: NEX pairwise spillover indexes



Note. This figure depicts the variations of the NEX pairwise spillover indexes, estimated with 250-day width rolling windows. We construct Efron percentile confidence intervals with 200 fixed-effect wild bootstraps. Smoothing splines are also applied to these intervals to improve their graphical readability. For more details on the smoothing method, see Green and Silverman (1994).

6 Robustness

The use of different specifications backs up our findings. We use the LASSO model to check that multicollinearity problems do not bias our results, as the instantaneous correlations between the variables are strong (Figure Ja).[14] We found that our spillover tables with and without shrinkage are very similar (Tables C, D). For example, the global interconnectedness (TSI) is 86.51 with VAR-OLS and 86.41 with VAR-LASSO. We further investigate the multicollinearity issue and show that the correlation coefficients between the model variables – the endogenous and lagged endogenous variables – are weak (Figure Jb). The VIF (Variance Inflation Factor) also highlights the result of no or weak multicollinearity; for all regressions, the VIFs barely exceed 1.[15] Finally, we provide readers with boxplots of the estimated parameters of the OLS-VAR model (Figure K), pointing out that all coefficients belong to their confidence intervals and that several variables are significant, e.g., discretionary consumption.[16]

7 Conclusion

As the demand for green investments increases, especially for green financial products, assessing interconnectedness between the green energy assets and the financial markets is of particular interest. We tackle this issue in the present paper by reasoning not only at an aggregate level but also at a sectoral level.

To this end, we focus on the world financial market and use the green energy stock index "WilderHill New Energy Global Innovation Index" (NEX) and the S&P Global 1200 sectoral stock indexes over the period from 2006-03-06 to 2020-06-19.

Using a wide range of robust methodologies, we find several key results. Concerning the static analysis, the green energy index has a significant degree of financial openness, and it receives more shocks than it transmits to other markets. The NEX interconnections are more substantial with the material and industrial indexes. We explain this result by the high degree of financial openness of these sectors and the similarity of the goods produced (or production processes) between the green, material, and technology industries.

Concerning the dynamic analysis, the system's global connectedness fluctuates depending on the occurrence of global shocks or economic/financial uncertainties. There was a sudden rise of interconnectedness during the pandemic crisis, reflecting the substantial market turmoil.

[14] Shrinkage methods with LASSO, ridge, or elastic-net allow to recover degrees of freedom and deal with potential multicollinearity problems by imposing constraints on the model coefficients (Friedman et al., 2008). By minimizing the variance forecast errors, we select the LASSO model with a constraint equal to 0.00123 (Figure I).

[15] Detailed results are available upon request.

[16] One could consider inference in the VAR-LASSO model based on recent bootstrap method specific to shrinking models (Dezeure et al., 2017). This is left for future research.

Moreover, the green energy index is mainly a net receiver of shocks from all economic sectors. Nevertheless, its spillover effects on other industries vary over time. For example, it rose during the pandemic crisis, illustrating the "flight to liquidity" mechanism. Investors abruptly withdraw their risky investments, such as green stocks, and move them to safer products. As a result, the interconnection with these risky assets increases.

Our findings have several implications for financial investors and governments. From a hedging perspective, if an investor seeks to reduce green energy assets' risks, he can diversify his portfolio by selecting stocks in the health care, utility, and consumer staple sectors due to the lowest interconnections with the green energy sector.

From a policy perspective, public authorities should keep in mind that green financial indexes are not free of market risks. The demand for these products is growing and must continue to accelerate if we want to reduce the "green finance gap."[17] Thus, the current and future spillovers of green energy returns to financial markets should not be overlooked. We expect more substantial spillovers to the material and industrial indexes.

Besides, if governments implement policies to reduce greenhouse gas emissions from the most polluting sectors, such as energy, industry, and materials (IPCC, 2014, fig 1.7), they have to consider potential feedback effects on green industries. Our findings suggest that a significant shock to the material or industrial sectors could have disruptive effects on the green sector; for example, implementing a low-carbon policy that abruptly changes the cost of (re)financing for these sectors. Such policies are of no doubt necessary, but we encourage policymakers to be cautious in their implementation. Yet, the risk of return spillover appears to be lower with the fossil fuel sector due to its lower interconnectedness with green industries.

Finally, there are several ways in which we can explore this issue further. We can analyze sectoral interconnection by focusing on a different geographical area (e.g., the United States). We can study whether the results vary by environmental sectors (e.g., energy efficiency, solar, or wind). Finally, we can deepen this analysis by shifting the focus from sectors to industry groups or industries.

[17] Green finance gap refers to the lack of required financial resources allocated to green investments (Orazio and Popoyan, 2019).

References

Acharya, V., R. Engle, and M. Richardson (2012). Capital shortfall: A new approach to ranking and regulating systemic risks. *American Economic Review 102*(3), 59–64.

Acharya, V. V., L. H. Pedersen, and M. Richardson (2010). Measuring Systemic Risk, Working Paper. *New York University, Stern School of Business*.

Adrian, T. and M. K. Brunnermeier (2011). COVAR. Working Paper 17454.

Ahmad, W. (2017). On the dynamic dependence and investment performance of crude oil and clean energy stocks. *Research in International Business and Finance 42*, 376–389.

Ahmad, W. and S. Rais (2018). Time-Varying Spillover and the Portfolio Diversification Implications of Clean Energy Equity with Commodities and Financial Assets. *Emerging Markets Finance and Trade 54*(8), 1838–1856.

Baruník, J. and T. Křehlík (2018). Measuring the frequency dynamics of financial connectedness and systemic risk. *Journal of Financial Econometrics 16*(2), 271–296.

Bhojraj, S., C. M. Lee, and D. K. Oler (2003). What's My Line? A Comparison of Industry Classification Schemes for Capital Market Research. *Journal of Accounting Research 41*(5), 745–774.

Billio, M., M. Getmansky, A. W. Lo, and L. Pelizzon (2012). Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *Journal of Financial Economics 104*(3), 535–559.

BloombergNEF (2020). Clean Energy Investment Trends 1H 2020. *Bloomberg New Energy Finance*.

Bondia, R., S. Ghosh, and K. Kanjilal (2016). International crude oil prices and the stock prices of clean energy and technology companies: Evidence from non-linear cointegration tests with unknown structural breaks. *Energy 101*, 558–565.

Broadstock, D. C., H. Cao, and D. Zhang (2012). Oil shocks and their impact on energy related stocks in China. *Energy Economics 34*(6), 1888–1895.

Campiglio, E. (2016). Beyond carbon pricing: The role of banking and monetary policy in financing the transition to a low-carbon economy. *Ecological Economics 121*, 220–230.

Candelon, B., L. Ferrara, and M. Joets (2020). Global Financial Interconnectedness: A Non-Linear Assessment of the Uncertainty Channel. *Applied Economics, Forthcoming*.

Dezeure, R., P. Bühlmann, and C. H. Zhang (2017). High-dimensional simultaneous inference with the bootstrap. *TEST 26*(4), 685–719.

Dickey, D. A. and W. A. Fuller (1981). Likelihood Ratio Statistics for Autoregressive Time Series with a Unit Root. *Econometrica 49*(4), 1057–1072.

Diebold, F. X. and K. Yilmaz (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. *The Economic Journal 119*, 158–171.

Diebold, F. X. and K. Yilmaz (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting 28*(1), 57–66.

Diebold, F. X. and K. Yilmaz (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics 182*(1), 119–134.

Diebold, F. X. and K. Yilmaz (2015). Financial and Macroeconomic Connectedness. *Oxford University Press*, 285.

Dutta, A., E. Bouri, D. Das, and D. Roubaud (2020). Assessment and optimization of clean energy equity risks and commodity price volatility indexes: Implications for sustainability. *Journal of Cleaner Production 243*, 118669.

Dutta, A., E. Bouri, and M. H. Noor (2018). Return and volatility linkages between CO2 emission and clean energy stock prices. *Energy 164*, 803–810.

Elie, B., J. Naji, A. Dutta, and G. S. Uddin (2019). Gold and crude oil as safe-haven assets for clean energy stock indices: Blended copulas approach. *Energy 178*, 544–553.

Engle, R. and B. Kelly (2012). Dynamic equicorrelation. *Journal of Business and Economic Statistics 30*(2), 212–228.

Faust, J. (1998). The robustness of identified VAR conclusions about money. *Carnegie-Rochester Conference Series on Public Policy 49*, 207–244.

Ferrer, R., S. J. H. Shahzad, R. López, and F. Jareño (2018). Time and frequency dynamics of connectedness between renewable energy stocks and crude oil prices. *Energy Economics 76*, 1–20.

Friedman, J., T. Hastie, and R. Tibshirani (2008). *The Elements of Statistical Learning (2nd Ed) Data Mining, Inference and Prediction.*

Gonçalves, S. and L. Kilian (2004). Bootstrapping autoregressions with conditional heteroskedasticity of unknown form. *Journal of Econometrics 123*, 89–120.

Green, P. and B. Silverman (1994). Nonparametric Regression and Generalized Linear Models: A Roughness Penalty Approach. *Chapman and Hall*, 1–184.

Henriques, I. and P. Sadorsky (2008). Oil prices and the stock prices of alternative energy companies. *Energy Economics 30*(3), 998–1010.

Hrazdil, K. and R. Zhang (2012). The importance of industry classification in estimating concentration ratios. *Economics Letters 114*(2), 224–227.

IEA (2016). World Energy Investment 2016. *International Energy Agency Report*.

IEA (2020). World Energy Investment 2020. *International Energy Agency Report*.

Inchauspe, J., R. D. Ripple, and S. Trück (2015). The dynamics of returns on renewable energy companies: A state-space approach. *Energy Economics 48*, 325–335.

Inderst, G., C. Kaminker, and F. Stewart (2012). Defining and Measuring Green Investments. *OECD Publishing 24*.

IPCC (2014). Climate Change 2014. *Intergovernmental Panel on Climate Change*, 1:169.

Jacomy, M., T. Venturini, S. Heymann, and M. Bastian (2014). ForceAtlas2, a continuous graph layout algorithm for handy network visualization designed for the Gephi software. *PLOS ONE 9*(6), 1–12.

Koop, G., M. Hashem Pesaran, and S. M. Potter (1996). Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics 74*, 19–147.

Kumar, S., S. Managi, and A. Matsuda (2012). Stock prices of clean energy firms, oil and carbon markets: A vector autoregressive analysis. *Energy Economics 34*(1), 215–226.

Kwiatkowski, D., P. C. Phillips, P. Schmidt, and Y. Shin (1992). Testing the null hypothesis of stationarity against the alternative of a unit root. How sure are we that economic time series have a unit root? *Journal of Econometrics 54*(1-3), 159–178.

Managi, S. and T. Okimoto (2013). Does the price of oil interact with clean energy prices in the stock market? *Japan and the World Economy 27*, 1–9.

Mignon, V. (2020). Effondrement des marchés financiers : le coronavirus n'explique pas tout. *The Conversation*, 1–5.

NEX Rule Book (2020). The WilderHill New Energy Global Innovation Index (NEX). *WilderHill New Energy Global Innovation Index*, 1–4.

Nobletz, C. (2021). Green Energy Indexes & Financial Markets: An In-Depth Look. *EconomiX Working Paper - Forthcoming*.

Orazio, P. D. and L. Popoyan (2019). Fostering green investments and tackling climate-related financial risks : Which role for macroprudential policies ? *Ecological Economics 160*(July 2018), 25–37.

Pham, L. (2019). Do all clean energy stocks respond homogeneously to oil price? *Energy Economics 81*, 355–379.

Phillips, P. C. B. and P. Perron (1988). Testing for a unit root in time series regression. *Biometrika 75*(2), 335–346.

Phillips, R. L. and R. Ormsby (2016). Industry classification schemes: An analysis and review. *Journal of Business and Finance Librarianship 21*(1), 1–25.

Reboredo, J. C. (2015). Is there dependence and systemic risk between oil and renewable energy stock prices? *Energy Economics 48*, 32–45.

Reboredo, J. C., M. A. Rivera-Castro, and A. Ugolini (2017). Wavelet-based test of co-movement and causality between oil and renewable energy stock prices. *Energy Economics 61*, 241–252.

Reboredo, J. C. and A. Ugolini (2018). The impact of energy prices on clean energy stock prices. A multivariate quantile dependence approach. *Energy Economics 76*, 136–152.

Sachs, J. D. (2015). Climate Change and Intergenerational Well-being. *Oxford handbook of the macroeconomics of global warming 52*(10), 52–5442–52–5442.

Sadorsky, P. (2012). Correlations and volatility spillovers between oil prices and the stock prices of clean energy and technology companies. *Energy Economics 34*(1), 248–255.

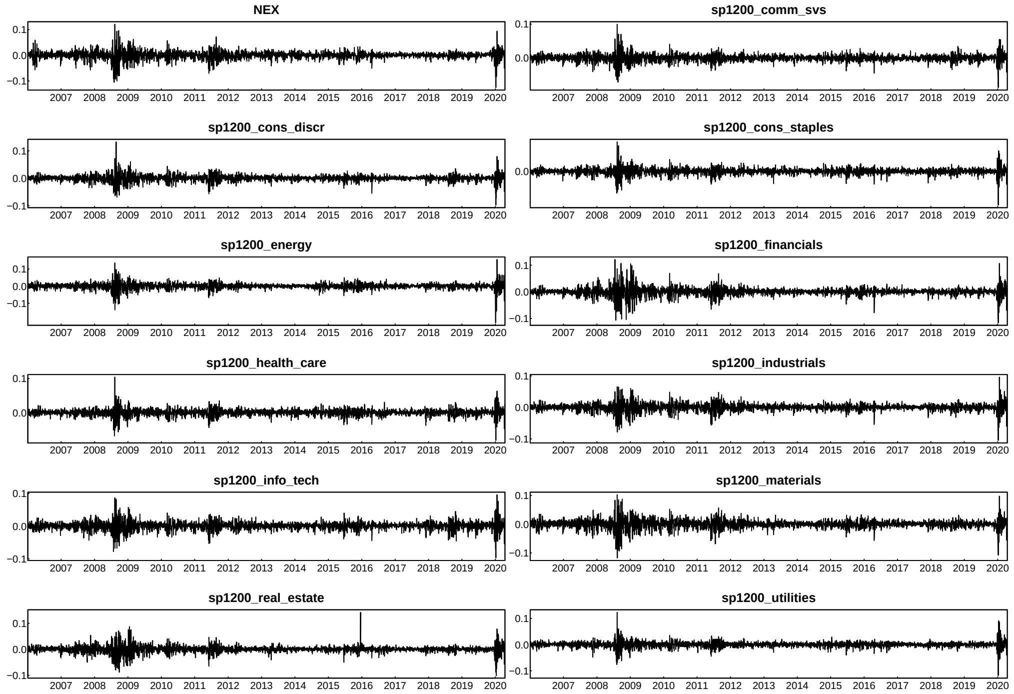
Sartzetakis, E. S. (2020, feb). Green bonds as an instrument to finance low carbon transition. *Economic Change and Restructuring*.

Sun, Y. (2004). A convergent t-statistic in spurious regressions. *Econometric Theory 20*(5), 943–962.

Wen, X., Y. Guo, Y. Wei, and D. Huang (2014). How do the stock prices of new energy and fossil fuel companies correlate? Evidence from China. *Energy Economics 41*, 63–75.

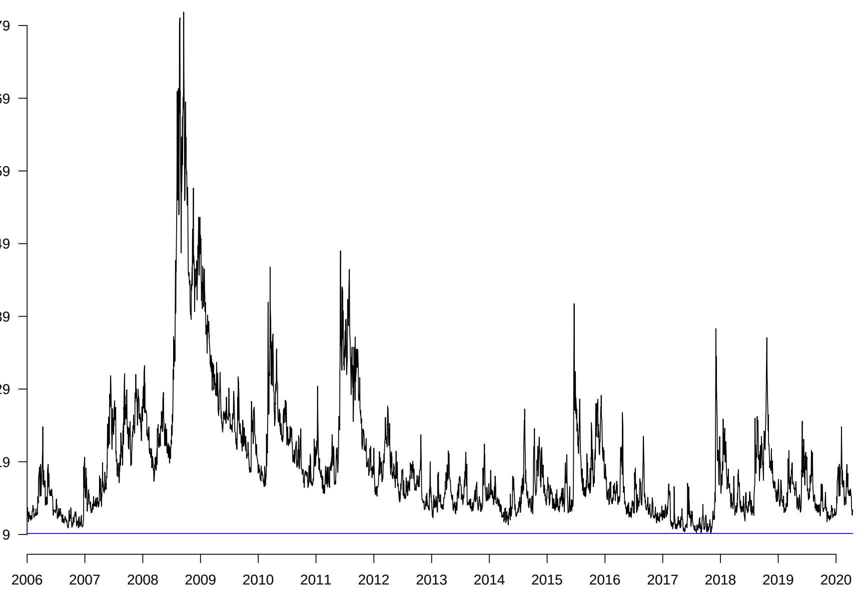
A Appendix

Figure A: Data in first logarithmic difference



Source. Datastream

Figure B: VIX (in level)



Note. The VIX is the volatility index of the S&P500 constructed by the CBOE (Chicago Board Options Exchange), and the blue line is drawn from the minimum point.

Table A: Unit root tests

	ADF	Model	PP	Model	KPSS	Model
NEX	-0.21	3	-0.19	3	4.67	1
sp1200_comm_svs	0.44	3	-2.54	2	1.68	1
sp1200_cons_discr	1.13	3	1.23	3	3.17	1
sp1200_cons_staples	1.59	3	1.65	3	2.56	1
sp1200_energy	-0.49	3	-0.48	3	1.78	1
sp1200_financials	-0.45	3	-0.44	3	4.77	1
sp1200_health_care	1.58	3	1.69	3	4.13	1
sp1200_industrials	0.55	3	0.63	3	2.96	1
sp1200_info_tech	1.92	3	2.01	3	5.47	1
sp1200_materials	-3.10*	2	-3.07*	2	0.71	1
sp1200_real_estate	0.38	3	0.41	3	3.64	1
sp1200_utilities	0.39	3	0.44	3	5.04	1
Δ NEX	-38.27*	3	-50.02*	3	0.12*	2
Δ sp1200_comm_svs	-23.74*	3	-58.47*	3	0.04*	2
Δ sp1200_cons_discr	-40.59*	3	-52.26*	3	0.09*	2
Δ sp1200_cons_staples	-44.67*	3	-58.22*	3	0.06*	2
Δ sp1200_energy	-33.73*	3	-58.46*	3	0.11*	2
Δ sp1200_financials	-41.01*	3	-53.98*	3	0.12*	2
Δ sp1200_health_care	-43.34*	3	-58.55*	3	0.13*	2
Δ sp1200_industrials	-40.46*	3	-52.36*	3	0.06*	2
Δ sp1200_info_tech	-42.74*	3	-58.61*	3	0.24*	2
Δ sp1200_materials	-41.22*	3	-50.46*	3	0.04*	2
Δ sp1200_real_estate	-39.33*	3	-54.78*	3	0.08*	2
Δ sp1200_utilities	-44.93*	3	-56.75*	3	0.08*	2

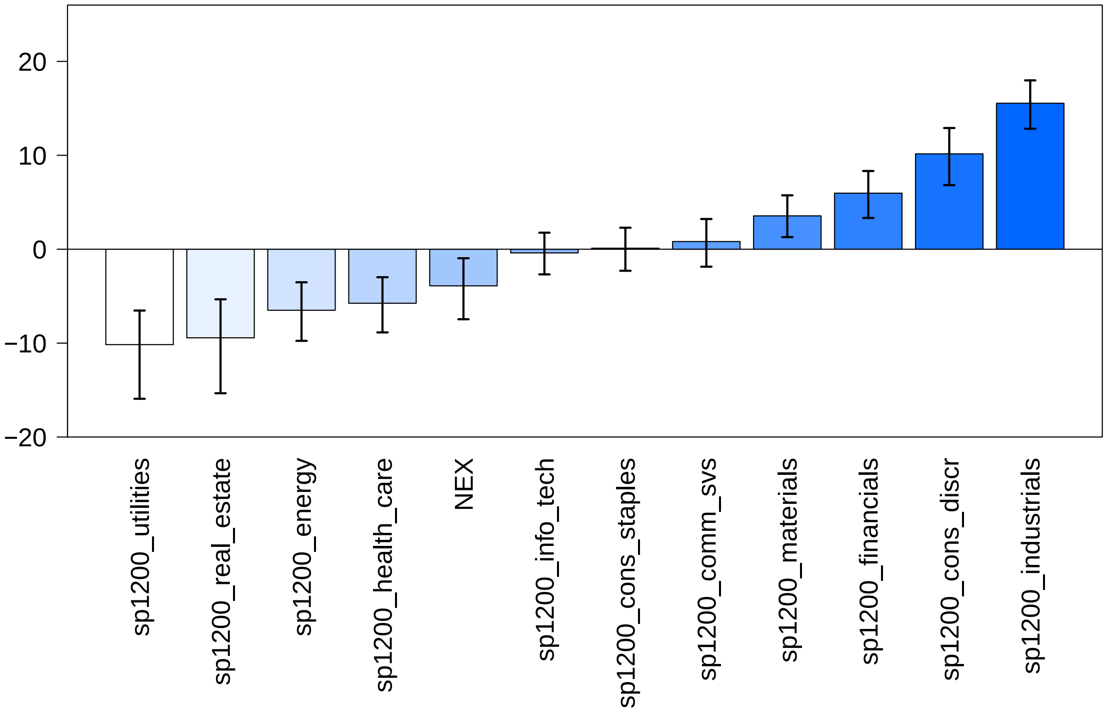
Note. ADF, the Augmented Dickey-Fuller test (Dickey and Fuller, 1981), PP, the Phillips-Perron test (Phillips-Perron, 1988), and KPSS, the Kwiatkowski-Phillips-Schmidt-Shin test (Kwiatkowski et al., 1992). For each test, we indicate the test statistic and the chosen model: 1 for trend and constant, 2 for constant, 3 without constant and trend. For the ADF and PP tests, the critical values at the 5% threshold for these three models are -3.41, -2.86, and -1.95, respectively. For the KPSS test, we test only the first two model specifications; the critical values at 5% are 0.146 and 0.463. The star indicates the stationarity of the variable at 5%. Note that the log of the S&P 1200 material index is, according to the ADF and PP tests, non-stationary at the 1% threshold but not at 5%.

Table B: Granger causality tests

Granger causality H0: the S&P Global 1200 does not Granger-cause the NEX Index F-Test = 17.668, df1 = 3, df2 = 3722, p-value = 0
Granger causality H0: the NEX Index does not Granger-cause the S&P Global 1200 F-Test = 10.679, df1 = 3, df2 = 3722, p-value = 0

Note. Each F-test follows a Fisher law with $(p, T - 2 * p - 1)$ degrees of freedom; $T = 3729$, $p = 3$. The critical values for these models are: 2.606 and 3.784 at 5% and 1% respectively.

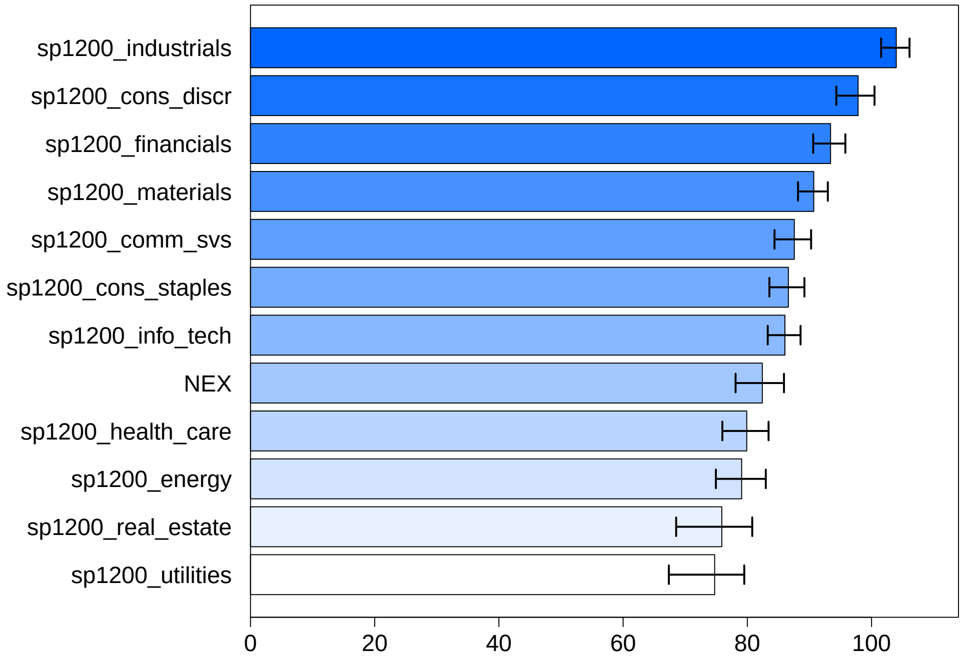
Figure C: Net indexes



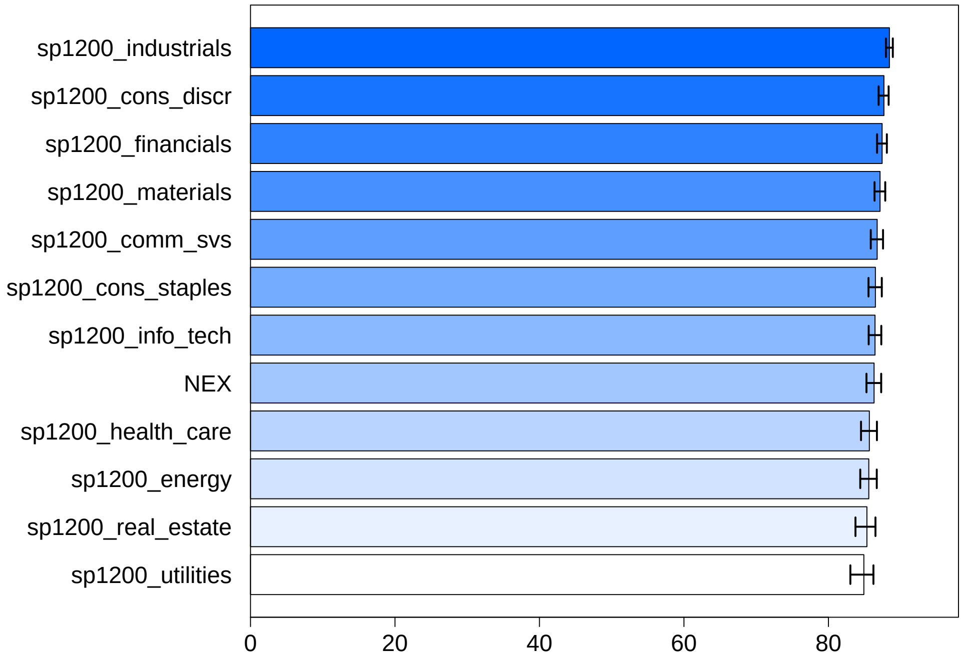
Note. This figure displays the net spillover indexes measured as the difference between the "to" and "from" indexes. If $net > 0$, the variable is a net transmitter of shocks, and if $net < 0$, the variable is a net receiver of shocks. The black lines depict the Efron percentile confidence intervals of these indexes, estimated with 5000 wild bootstraps.

Figure D: Directional spillover indexes

(a) To indexes



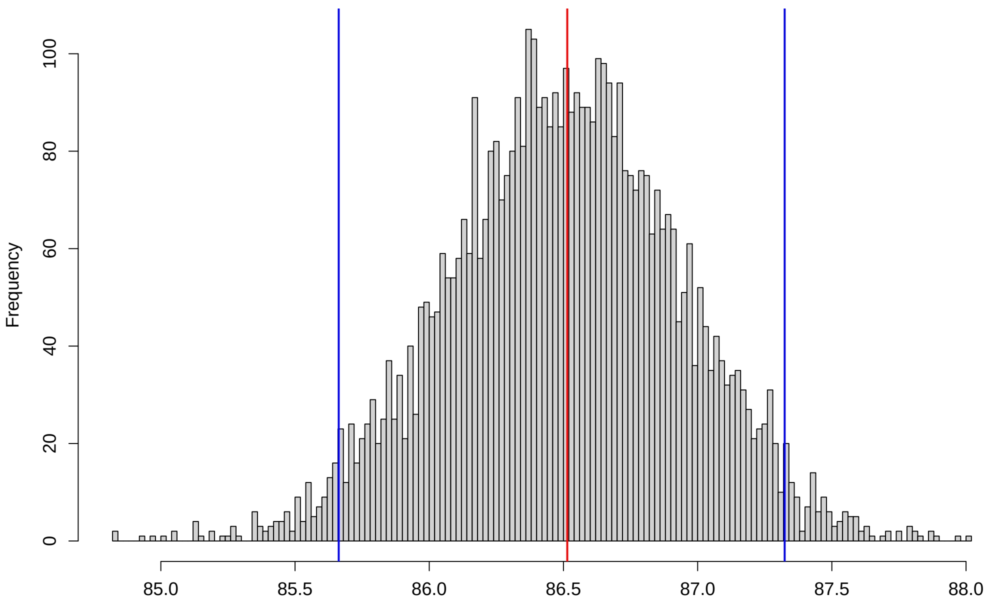
(b) From indexes



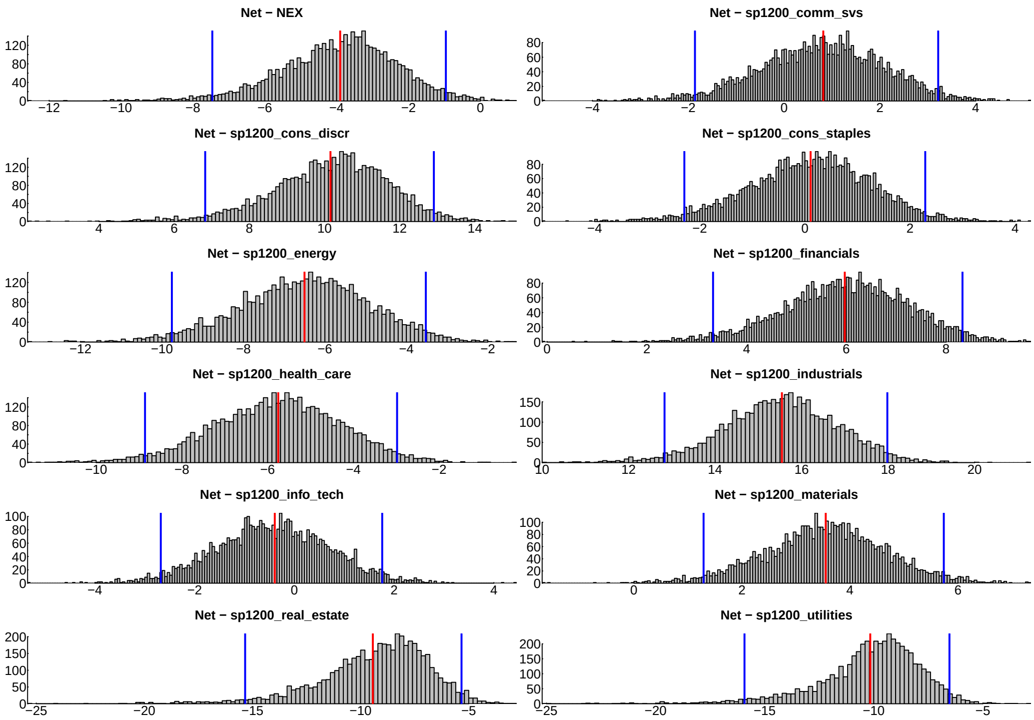
Note. These figures display the directional spillover indexes. The "to" indexes are the variance shares that variables transmit to others. Conversely, the "from" indexes are the variance shares that variables receive from others. The black lines represent the Efron percentile confidence intervals around these indexes, estimated with 5000 wild bootstraps.

Figure E: TSI and Net indexes' distributions

(a) Total Spillover Index



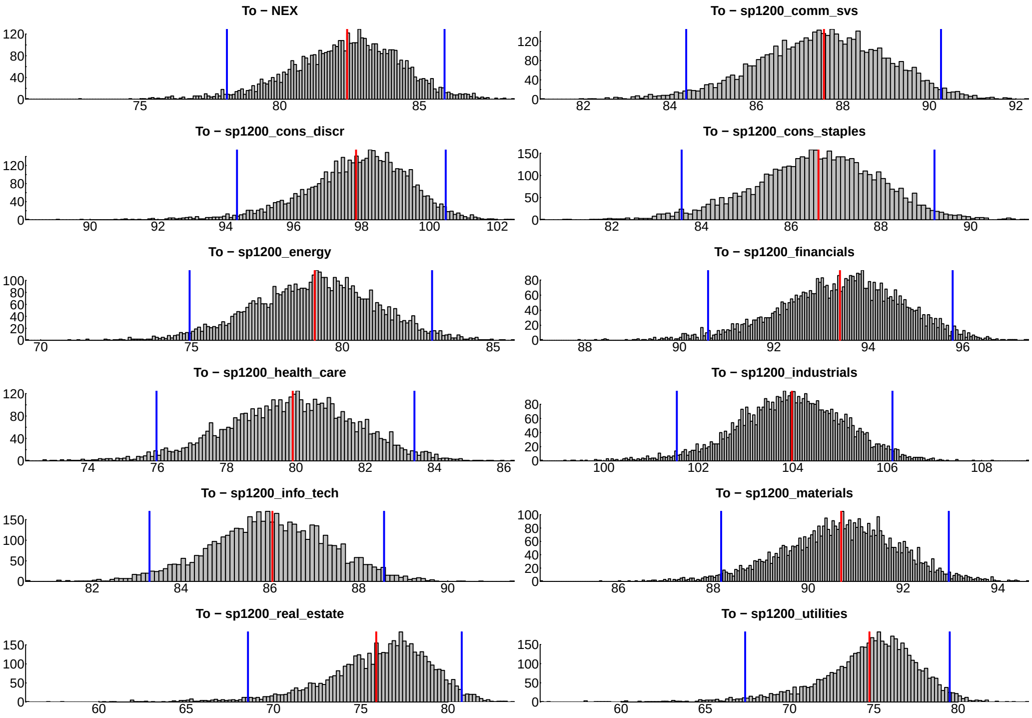
(b) Net indexes



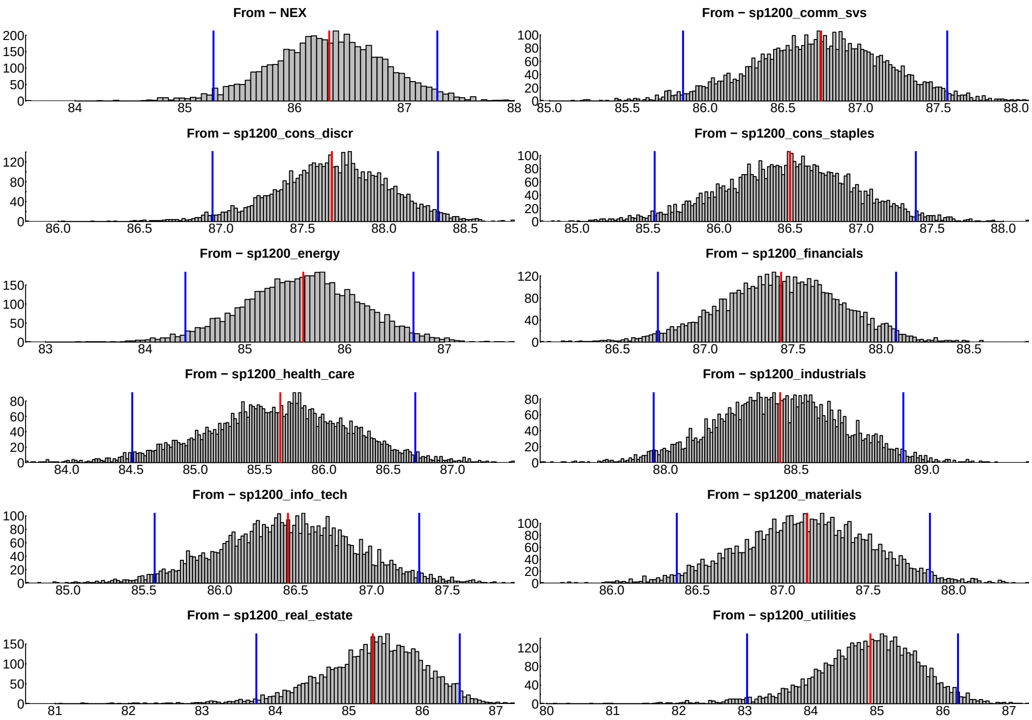
Note. The spillover indexes' distribution is achieved with 5000 wild bootstraps. The blue bars are the Efron percentile confidence intervals – 2.5% and 97.5% distributions quantiles. The red bars are the OLS indexes estimated with the VAR model.

Figure F: Directional spillover index distributions

(a) To indexes

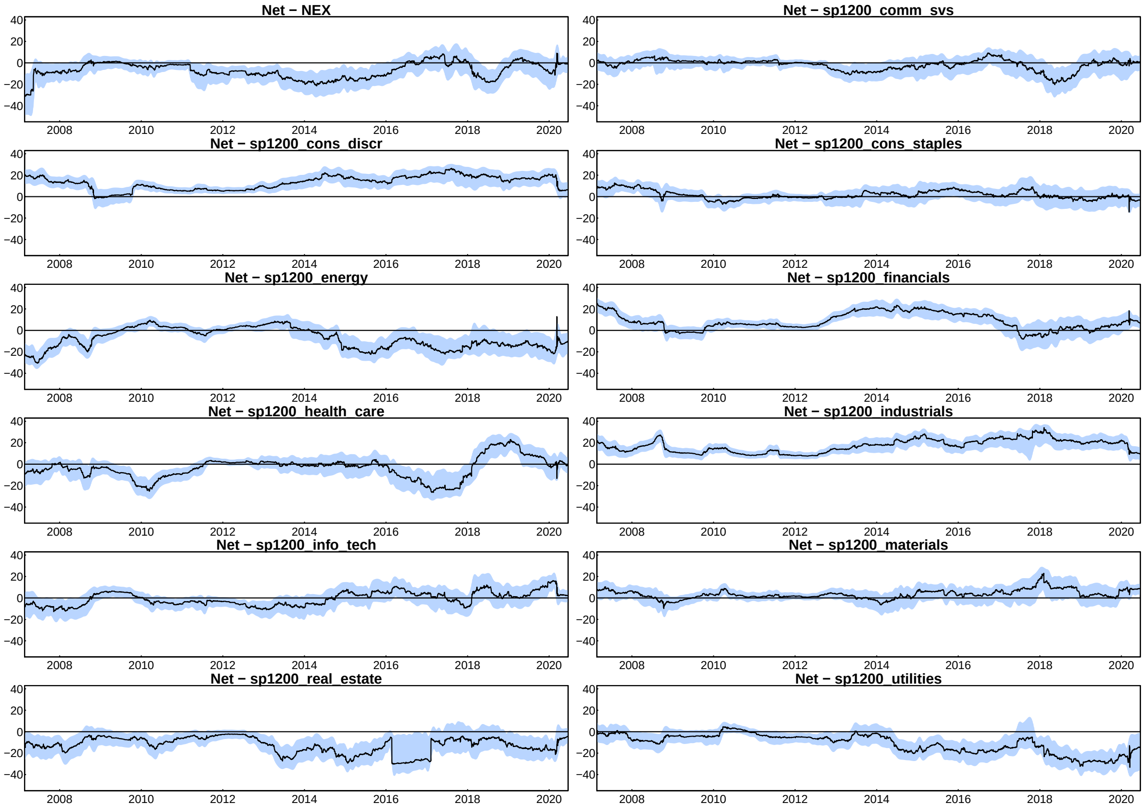


(b) From indexes



Note. The spillover indexes' distribution is achieved with 5000 wild bootstraps. The blue bars are the Efron percentile confidence intervals – 2.5% and 97.5% distributions quantiles. The red bars are the OLS indexes estimated with the VAR model.

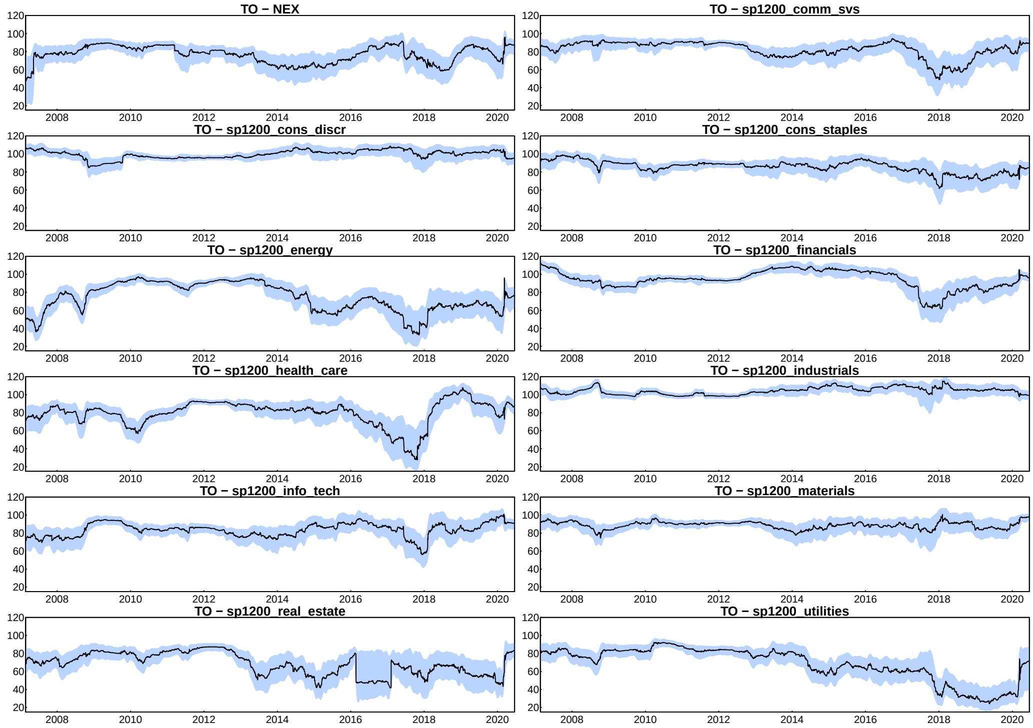
Figure G: NET indexes over time



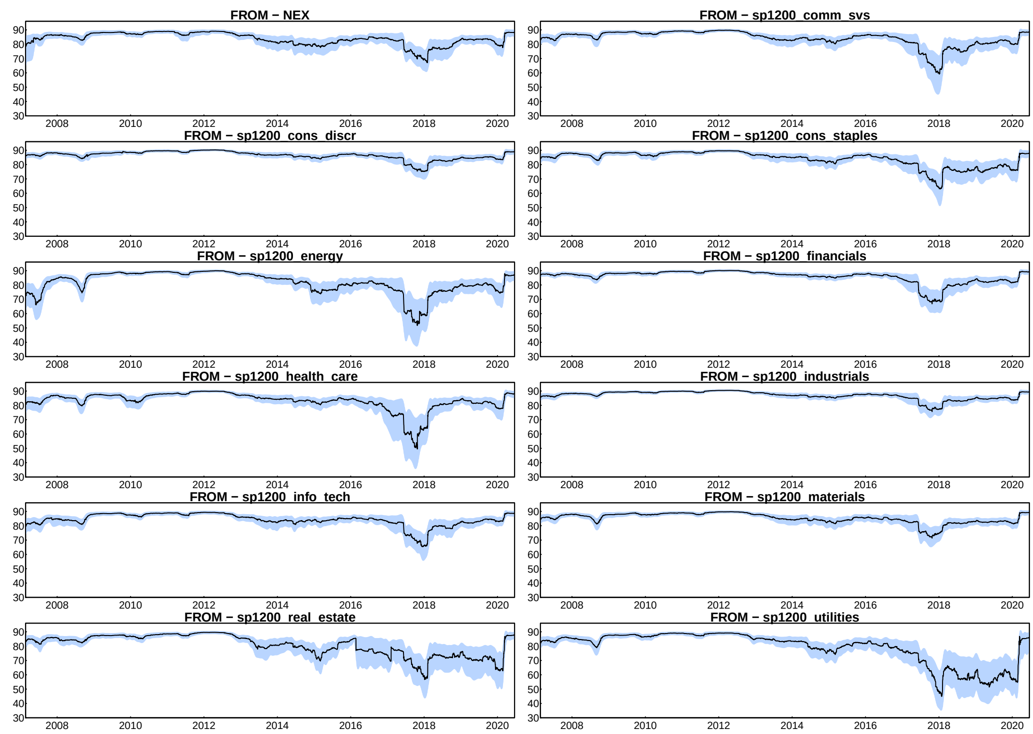
Note. This figure depicts the variations of the NET spillover indexes, estimated with 250-day width rolling windows. We construct Efron percentile confidence intervals with 200 fixed-effect wild bootstraps. Smoothing splines are also applied to these intervals to improve their graphical readability. For more details on the smoothing method, see Green and Silverman (1994).

Figure H: Directional spillover indexes over time

(a) To indexes



(b) From indexes



Note. This figure depicts the variations of the directional spillover indexes, estimated with 250-day width rolling windows. We construct Efron percentile confidence intervals with 200 fixed-effect wild bootstraps. Smoothing splines are also applied to these intervals to improve their graphical readability. For more details on the smoothing method, see Green and Silverman (1994).

Table C: VAR-OLS Spillover Table

	NEX	Comm_svs	Cons_discr	Cons_staples	Energy	Financials	Health_care	Industrials	Info_tech	Materials	Real_estate	Utilities	from
NEX	13.68	7.52	8.86	6.5	7.84	8.80	6.24	9.78	8.13	9.69	6.9	6.05	86.32
	12.70 14.74	7.12 7.89	8.28 9.34	5.98 6.97	7.36 8.29	8.45 9.13	5.68 6.81	9.43 10.10	7.77 8.48	9.35 10.06	6.18 7.47	5.10 6.75	85.26 87.29
Comm_svs	7.21	13.25	8.84	8.73	7.12	8.35	7.72	8.84	7.73	7.96	6.38	7.87	86.75
	6.70 7.65	12.44 14.14	8.41 9.16	8.29 9.10	6.64 7.57	7.96 8.70	7.21 8.17	8.52 9.11	7.34 8.09	7.57 8.31	5.62 6.97	7.21 8.37	85.86 87.55
Cons_discr	7.64	8.05	12.32	7.89	6.59	9.02	7.41	10.27	9.33	8.10	7.60	5.77	87.68
	7.07 8.07	7.68 8.39	11.67 13.05	7.49 8.33	6.13 7.04	8.47 9.39	7.02 7.75	9.95 10.59	9.02 9.67	7.68 8.42	6.85 8.11	4.82 6.38	86.94 88.33
Cons_staples	6.25	8.82	8.74	13.50	6.47	7.54	9.26	8.78	7.39	7.19	6.92	9.13	86.5
	5.65 6.78	8.35 9.21	8.39 9.08	12.61 14.45	5.86 7.04	7.04 7.96	8.76 9.71	8.47 9.04	6.95 7.76	6.71 7.60	6.07 7.52	8.69 9.56	85.54 87.38
Energy	8.05	7.73	7.85	6.91	14.42	8.47	6.69	9.51	7.40	10.11	5.93	6.94	85.58
	7.51 8.51	7.26 8.15	7.38 8.23	6.37 7.43	13.31 15.59	8.05 8.83	6.10 7.21	9.18 9.82	6.96 7.78	9.61 10.63	5.20 6.57	6.06 7.620	84.40 86.68
Financials	8.02	7.88	9.40	7.06	7.38	12.57	6.85	10.28	7.85	8.46	8.17	6.08	87.43
	7.63 8.34	7.48 8.25	8.79 9.85	6.55 7.46	6.94 7.78	11.91 13.27	6.33 7.30	9.95 10.63	7.48 8.18	8.09 8.84	7.37 8.73	5.44 6.59	86.72 88.08
Health_care	6.38	8.30	8.72	9.84	6.65	7.78	14.34	8.82	8.40	6.85	6.23	7.68	85.66
	5.80 6.92	7.81 8.74	8.32 9.08	9.39 10.28	6.06 7.19	7.25 8.23	13.28 15.49	8.45 9.14	7.98 8.77	6.34 7.30	5.47 6.85	6.91 8.31	84.50 86.71
Industrials	8.16	7.66	9.80	7.50	7.64	9.41	7.09	11.56	8.37	9.15	7.30	6.35	88.44
	7.81 8.46	7.29 7.96	9.40 10.14	7.15 7.80	7.27 7.97	9.13 9.69	6.71 7.44	11.09 12.04	8.09 8.62	8.89 9.41	6.60 7.74	5.61 6.87	87.95 88.90
Info_tech	7.73	7.83	10.29	7.41	6.93	8.38	7.93	9.71	13.55	7.84	6.88	5.52	86.45
	7.30 8.11	7.46 8.18	9.88 10.70	6.97 7.79	6.45 7.34	8.02 8.70	7.47 8.32	9.41 10.00	12.68 14.42	7.47 8.16	6.20 7.38	4.80 6.14	85.57 87.31
Materials	8.96	7.70	8.71	6.87	9.09	8.66	6.16	10.19	7.66	12.86	6.60	6.54	87.14
	8.52 9.34	7.28 8.07	8.20 9.07	6.35 7.32	8.63 9.51	8.30 9.00	5.62 6.66	9.83 10.54	7.29 7.99	12.13 13.62	5.91 7.13	5.89 7.06	86.37 87.86
Real_estate	7.39	7.14	9.42	7.66	6.09	9.69	6.45	9.45	7.61	7.61	14.68	6.82	85.32
	6.85 7.91	6.62 7.58	8.97 9.92	7.12 8.10	5.47 6.67	9.22 10.16	5.88 6.94	9.13 9.78	7.16 8.03	7.15 8.02	13.49 16.25	5.57 7.53	83.74 86.50
Utilities	6.62	8.93	7.21	10.24	7.29	7.31	8.09	8.35	6.19	7.71	6.97	15.1	84.9
	5.87 7.23	8.43 9.40	6.46 7.70	9.65 10.95	6.53 7.91	6.82 7.74	7.44 8.70	7.89 8.69	5.60 6.71	7.24 8.11	5.88 7.80	13.77 16.96	83.03 86.22
TO	82.41	87.56	97.84	86.61	79.08	93.4	79.91	103.98	86.06	90.69	75.89	74.74	
	78.11 85.9	84.38 90.27	94.33 100.48	83.56 89.19	74.94 82.97	90.61 95.79	75.98 83.42	101.54 106.11	83.29 88.57	88.16 92.96	68.54 80.79	67.37 79.5	**TSI**
NET	-3.9	0.82	10.16	0.11	-6.5	5.97	-5.75	15.54	-0.39	3.55	-9.44	-10.16	**86.51**
	-7.45 -0.96	-1.86 3.21	6.82 12.90	-2.29 2.28	-9.75 -3.52	3.32 8.32	-8.86 -2.98	12.82 17.98	-2.67 1.76	1.28 5.73	-15.34 -5.33	-15.92 -6.53	**85.66 87.32**

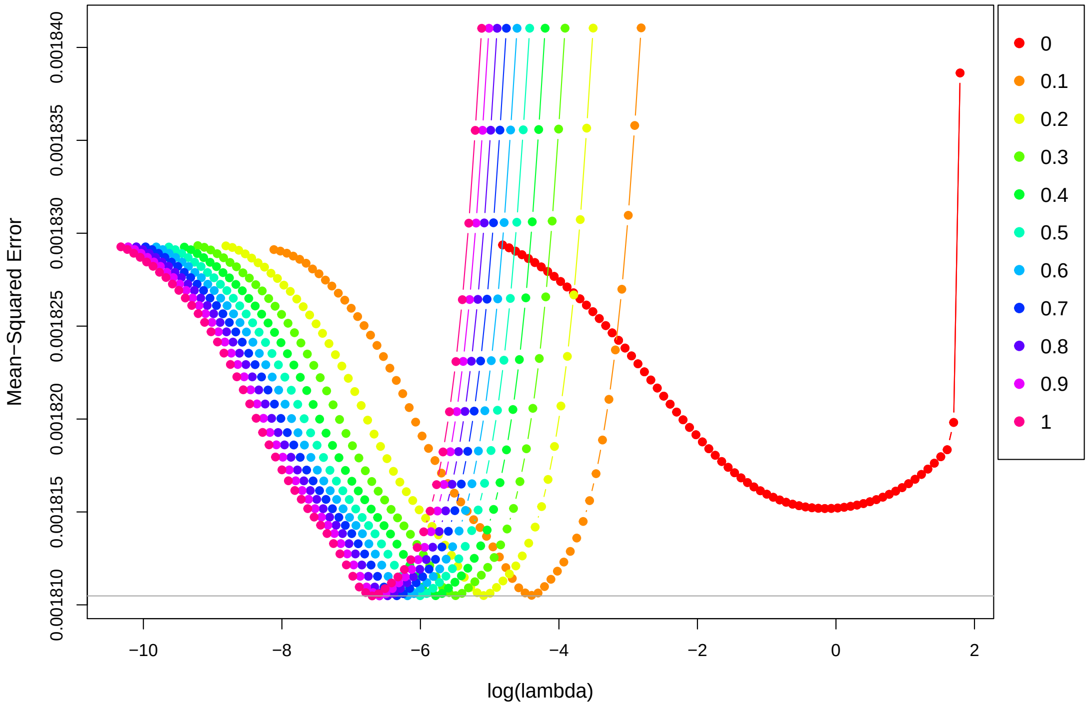
Note. The first row displays the coefficients of the generalized forecast error variance decomposition. The second row shows the Efron percentile confidence intervals for these coefficients. Pairwise connectedness ij is the estimated contribution to the forecast error variance of market i from market shocks (innovations) j, for all i and j. Therefore, the diagonal elements of the forecast error variance are the "own-asset shocks" (or "own-variance shares"). The sum of the off-diagonal columns ("to") and the sum of the off-diagonal rows ("from") are respectively the "directional spillovers to others" and the "directional spillovers from others." The difference between the "to" and the "from" depicts the net spillover indexes. The Total Spillover Index ("TSI") at the bottom right of the spillover table is the off-diagonal column sum (or off-diagonal row sum) divided by the column sum (or row sum).

Table D: VAR-LASSO Spillover table

	NEX	Comm_svs	Cons_discr	Cons_staples	Energy	Financials	Health_care	Industrials	Info_tech	Materials	Real_estate	Utilities	from
NEX	13.82	7.56	8.78	6.47	7.77	8.84	6.22	9.87	7.95	9.73	6.89	6.11	86.18
Comm_svs	7.19	13.37	8.8	8.79	7.11	8.36	7.75	8.81	7.66	7.88	6.37	7.91	86.63
Cons_discr	7.58	8.07	12.31	7.88	6.63	9.07	7.38	10.3	9.31	8.06	7.67	5.73	87.69
Cons_staples	6.2	8.92	8.71	13.59	6.43	7.55	9.3	8.74	7.36	7.1	6.9	9.19	86.41
Energy	8.07	7.73	7.85	6.88	14.52	8.43	6.64	9.56	7.39	10.14	5.9	6.89	85.48
Financials	7.97	7.93	9.39	7.06	7.35	12.65	6.81	10.31	7.83	8.41	8.25	6.05	87.35
Health_care	6.35	8.39	8.68	9.91	6.6	7.76	14.48	8.79	8.37	6.76	6.2	7.71	85.52
Industrials	8.15	7.66	9.77	7.49	7.63	9.44	7.08	11.62	8.33	9.14	7.34	6.34	88.38
Info_tech	7.65	7.81	10.33	7.39	6.94	8.39	7.89	9.75	13.65	7.78	6.95	5.47	86.35
Materials	9.07	7.7	8.64	6.84	9.06	8.67	6.13	10.28	7.5	12.94	6.59	6.57	87.06
Real_estate	7.32	7.14	9.39	7.61	6.09	9.73	6.44	9.47	7.66	7.54	14.85	6.76	85.15
Utilities	6.64	9.02	7.12	10.31	7.23	7.28	8.12	8.33	6.12	7.7	6.91	15.23	84.77
to	82.2	87.92	97.46	86.63	78.85	93.51	79.77	104.21	85.48	90.24	75.96	74.73	**TSI**
net	-3.98	1.29	9.77	0.22	-6.63	6.16	-5.75	15.82	-0.87	3.18	-9.18	-10.05	**86.41**

Note. Pairwise connectedness ij is the estimated contribution to the forecast error variance of market i from market shocks (innovations) j, for all i and j. Therefore, the diagonal elements of the forecast error variance are the "own-asset shocks" (or "own-variance shares"). The sum of the off-diagonal columns ("to") and the sum of the off-diagonal rows ("from") are respectively the "directional spillovers to others" and the "directional spillovers from others." The difference between the "to" and the "from" depicts the net spillover indexes. The Total Spillover Index ("TSI") at the bottom right of the spillover table is the off-diagonal column sum (or off-diagonal row sum) divided by the column sum (or row sum).

Figure I: Shrinking method (α) and penalty parameter (λ) selection process



Note. This graph depicts the results of the forecast error cross-validation with 10-folds. In y-axis, we have the Mean Squared Error (MSE) values, while in x-axis, we have the log values of λ. The color curves are the λ-MSE for each α specification: $\alpha = 0$, ridge ; $\alpha = 1$, LASSO ; $\alpha \in]0, 1[$ = elastic net.

Figure J: Correlation coefficient matrix

(a) Instantaneous correlation coefficient matrix

	NEX	sp1200_comm_svs	sp1200_cons_discr	sp1200_cons_staples	sp1200_energy	sp1200_financials	sp1200_health_care	sp1200_industrials	sp1200_info_tech	sp1200_materials	sp1200_real_estate	sp1200_utilities
sp1200_utilities	0.66	0.77	0.68	0.82	0.69	0.69	0.73	0.74	0.63	0.71	0.67	1
sp1200_real_estate	0.71	0.69	0.79	0.71	0.64	0.81	0.65	0.8	0.71	0.72	1	0.67
sp1200_materials	0.84	0.76	0.81	0.72	0.83	0.82	0.67	0.89	0.75	1	0.72	0.71
sp1200_info_tech	0.74	0.76	0.87	0.74	0.71	0.78	0.76	0.84	1	0.75	0.71	0.63
sp1200_industrials	0.84	0.81	0.92	0.8	0.81	0.9	0.77	1	0.84	0.89	0.8	0.74
sp1200_health_care	0.65	0.76	0.77	0.83	0.68	0.73	1	0.77	0.76	0.67	0.65	0.73
sp1200_financials	0.8	0.79	0.86	0.74	0.76	1	0.73	0.9	0.78	0.82	0.81	0.69
sp1200_energy	0.74	0.73	0.73	0.69	1	0.76	0.68	0.81	0.71	0.83	0.64	0.69
sp1200_cons_staples	0.67	0.81	0.8	1	0.69	0.74	0.83	0.8	0.74	0.72	0.71	0.82
sp1200_cons_discr	0.79	0.81	1	0.8	0.73	0.86	0.77	0.92	0.87	0.81	0.79	0.68
sp1200_comm_svs	0.73	1	0.81	0.81	0.73	0.79	0.76	0.81	0.76	0.76	0.69	0.77
NEX	1	0.73	0.79	0.67	0.74	0.8	0.65	0.84	0.74	0.84	0.71	0.66

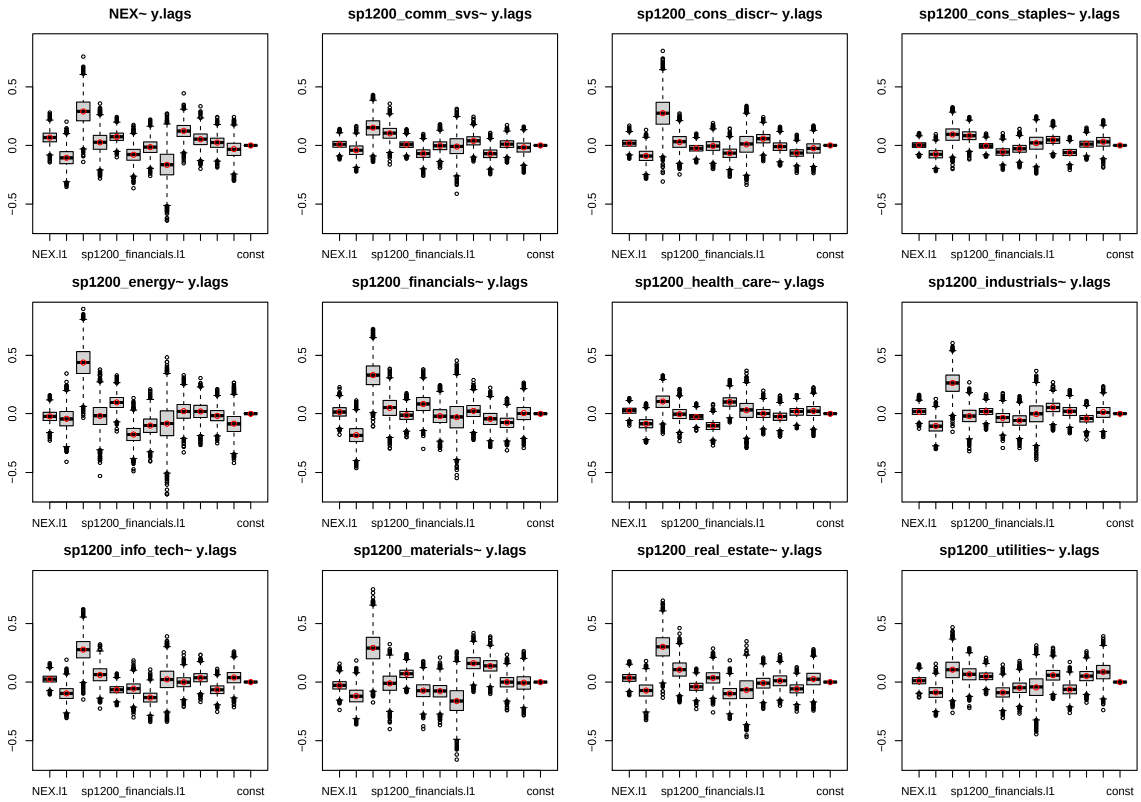
Corr
1.0
0.5
0.0
−0.5
−1.0

(b) Correlation coefficient matrix of the VAR model variables

	NEX	sp1200_comm_svs	sp1200_cons_discr	sp1200_cons_staples	sp1200_energy	sp1200_financials	sp1200_health_care	sp1200_industrials	sp1200_info_tech	sp1200_materials	sp1200_real_estate	sp1200_utilities
sp1200_utilities.l1	0.14	0.04	0.05	0.03	−0.01	0.07	0.01	0.09	0.02	0.11	0.1	0.07
sp1200_real_estate.l1	0.17	0.05	0.08	0.03	0.02	0.09	0.01	0.11	0.02	0.14	0.11	0.06
sp1200_materials.l1	0.2	0.02	0.1	−0.01	0.04	0.09	−0.01	0.14	0.04	0.18	0.12	0.03
sp1200_info_tech.l1	0.21	0.07	0.13	0.04	0.05	0.12	0.02	0.15	0.04	0.19	0.13	0.06
sp1200_industrials.l1	0.2	0.05	0.12	0.02	0.03	0.12	0.01	0.15	0.04	0.17	0.13	0.05
sp1200_health_care.l1	0.16	0.06	0.08	0.03	0.01	0.09	0.04	0.1	0	0.13	0.1	0.05
sp1200_financials.l1	0.18	0.03	0.11	0	0.01	0.12	−0.02	0.13	0.02	0.15	0.13	0.03
sp1200_energy.l1	0.19	0.03	0.08	0	0.04	0.08	−0.02	0.12	0	0.17	0.09	0.05
sp1200_cons_staples.l1	0.17	0.07	0.09	0.05	0.01	0.1	0.02	0.11	0.03	0.13	0.12	0.07
sp1200_cons_discr.l1	0.22	0.08	0.15	0.04	0.07	0.14	0.02	0.17	0.07	0.19	0.16	0.06
sp1200_comm_svs.l1	0.16	0.04	0.08	0.01	0.02	0.08	−0.01	0.1	0.01	0.13	0.11	0.04
NEX.l1	0.2	0.04	0.11	0.01	0.03	0.1	0.01	0.14	0.04	0.15	0.12	0.04

Corr
1.0
0.5
0.0
−0.5
−1.0

Figure K: Boxplots of the VAR-OLS coefficients



Note. This figure shows the boxplots of the VAR-OLS estimated parameters for all y. The red dots depict the OLS estimated parameters, while the gray bands display the Efron Percentile confidence intervals computed with 5000 wild-bootstrap. The lagged endogenous variables are in order: NEX.l1, sp1200_comm_svs.l1, sp1200_cons_discr.l1, sp1200_cons_staples.l1, sp1200_energy.l1, sp1200_financials.l1, sp1200_health_care.l1, sp1200_industrials.l1, sp1200_info_tech.l1, sp1200_materials.l1, sp1200_real_estate.l1, sp1200_utilities.l1.