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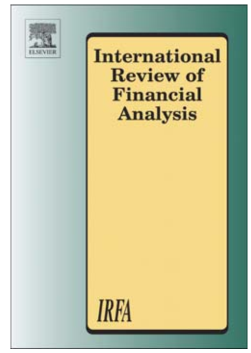

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Mark Cummins*
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September 30, 2014

Abstract

Covering the first commitment period of the Kyoto Protocol (2008-2012), we perform a price discovery analysis to determine Granger causality relationships for a range of prominent green equity indices with the broader equity and commodity markets. Three pivotal contributions are made. Firstly, an expanded database is used that gives greater depth to the price discovery analysis relative to previous literature. Prominent global, regional and sectoral green equity indices are considered, as well as a broader set of commodities including crude oil, natural gas and emissions. The inclusion of natural gas recognises its role as the transition fossil fuel to a low carbon economy. In addition to the main European Union Allowance traded under the EU Emissions Trading Scheme, Certified Emissions Reduction (CER) prices are also included in the emissions database to capture activities under the global Clean Development Mechanism. Secondly, a problem with conventional symmetric vector autoregression is that its implementation commonly leads to large occurrences of insignificant parameters. Therefore, as a first layer of robustness, we utilise an asymmetric vector autoregression model to perform the Granger causality testing, which addresses this limitation by means of allowing different lag specifications among the system variables. Thirdly, explicit recognition is made in our study of the *multiple comparisons bias* inherent in our high-dimensional testing framework, which is the non-negligible likelihood of

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identifying statistically significant results by pure chance alone. As a second layer of robustness, we utilise a *generalised* Holm correction method to control this source of bias. At conventional statistical significance levels, we find that the FTSE 100 and FTSE Global Small Cap equity indices have a causal effect on all of the green equity indices, with limited evidence of causality in the opposite direction. Within the green equity markets, we find evidence that the chosen sectoral index has a Granger causal effect on one of the two global indices considered and also the regional index. This price transmission provides modest evidence that the global green economy is becoming ever more integrated. NBP gas is shown to have a causal effect on all of the green equity indices, whereas we find no such evidence for Brent oil. The former observation may reflect the increasing role of gas as the transition fuel to a low carbon economy, playing a key role in decisions on power generation mix and associated capital investment. Finally, we find no evidence that EUA or CER emissions prices have a causal effect on green stocks, consistent with previous findings and likely reflecting the excessively low prices being commanded for compliance permits in the European emissions markets.

Keywords: green equity indices; asymmetric vector autoregression; Granger causality; multiple hypothesis testing; multiple comparisons bias.

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1 Introduction

The 2013 report of the Frankfurt School-United Nations Environment Programme Collaborating Centre for Climate and Sustainable Energy Finance (herein referred to as the FS-UNEP 2013 report) on global trends in renewable energy investment describes 2012 as a particularly challenging year. Overall new investment in renewable energy in 2012 was down 12% on 2011 levels to $244bn, after an almost sustained period of double digit growth since 2004 (with 2009 being the only exception to this). The public markets saw the most dramatic levels of relative decline. Investment fell approximately 61%, from $10.6bn in 2011 to $4.1bn in 2012. Of the two primary renewable energy types, i.e. wind and solar, new public market investment fell 72% and 50% respectively. The absolute levels of public market investment have consistently been dwarfed by the level of asset finance investment for the utility-scale roll out of renewable energy, which in 2012 was $149bn; 36 times that of the public market investment. This highlights the major challenge in attracting private institutional finance to renewable energy and clean technology companies. Indeed, the green equity sector has substantially underperformed the broader equity markets over recent years. Given this difference in equity market performance, we conduct a price discovery analysis to determine what interactions exist both within the green equity sector and between this sector and the broader equity and commodity markets, where in the latter we include oil, natural gas and emissions.

The two prominent studies in this space are Henriques & Sadorsky (2008) and Kumar et al. (2012). The focus of these studies has predominately been on the relationship between the stock prices of clean energy companies and oil or technology companies. Henriques & Sadorsky (2008), using Wilder Hill Clean Energy Index data and a vector autoregression model, studied the dynamic relationship between the stock prices of alternative energy companies, oil prices, interest rates and the Arca Tech 100 index of technology companies. Interestingly the authors find that shocks to technology company stock prices have a larger impact on the stock prices of alternative energy companies than oil prices. They noted that the success of alternative energy companies often depends upon the success or failure of specific technologies; therefore, they have more in common with technology companies than fossil fuel based energy companies. This relationship with technology firms was also found by Kumar et al. (2012) who expanded on the literature in considering carbon prices in addition to oil and technology stocks. Kumar et al. (2012) include three indexes in their research: the Wilder Hill New Energy Global Innovation Index; the Wilder Hill Clean Energy Index; and the S&P Global Clean Energy Index. The authors confirm that clean energy stock prices are influenced by oil prices, interest rates and technology stock prices but perhaps surprisingly not by the prices of carbon allowances. Other related literature includes Boulatoff and Boyer (2009), Sadorsky (2011), Sabbaghi (2011) and Bohl et al. (2013).

As a first contribution, we use an expanded database of green equity indices, broader equity market indices and commodities for the price discovery analysis in our study, which offers notable benefits. Specifically, the suite of green equity indices extends previous literature by including global, sectoral and regional indices. As set out above, Henriques & Sadorsky (2008) consider one global index in their study and Kumar et al. (2012) consider three specific global indices. Our study extends this literature in considering two prominent global indices, one regional index and one sectoral index. The indices are drawn from the following index series: Bloomberg New Energy Finance Clean Energy Indices; FTSE Environmental Markets Indices; and Wilderhill Indices. This extended database allows for greater depth in determining general global, regional and sectoral price transmission. The commodities database also extends previous literature by means of considering natural gas market information, where previously only oil has been considered. The motivation for the inclusion of natural gas is centred on the recognition that natural gas is seen as the transition fossil fuel to a low carbon economy. The emissions market data in our study additionally extends on previous literature by means of considering Certified Emissions Reduction (CER) prices, along with the prices of the primary compliance unit of the European Union Allowance (EUA) within the EU Emissions Trading Scheme. CERs are awarded against projects funded and developed under the global Clean Development Mechanism (CDM) as set out under the Kyoto protocol. As the CDM encourages private investment from developed nations into renewable energy and clean technology projects in developing nations, the CER prices are included here as a measure of this activity as it would be reasonably expected that some of the constituent companies within the green equity indices considered in our study would be involved in the CDM markets.

As a second contribution, the methodology employed in our analysis extends previous literature, which has applied the conventional vector autoregression (VAR) model to perform its analysis (Henriques & Sadorsky, 2008; Kumar et al., 2012). A limitation of VAR is that the symmetrical nature of the model specification is such that its implementation often leads to the estimation of a large number of insignificant coefficients (Keating, 2000). Much of the literature that implements VAR models overlooks this issue, although it has been recognised as a problem since the seminal work of Sims (1980). Hsiao (1981) and Litterman (1986) propose Bayesian approaches the seek to constrain the VAR coefficients in an effort to achieve more efficient estimates (Keating, 2000). In contrast to these approaches, Keating (2000) proposes a flexible methodology, which allows for asymmetry in the specification of the vector autoregression model. Within an asymmetric vector autoregression (AVAR), each equation of the model system contains the same variables, ensuring that parameter estimates are both consistent and efficient, but the difference over conventional symmetric VAR models is that the lags of the variables are allowed to potentially differ. Keating (2000) notes that parameter estimates from AVAR models generally have smaller standard errors. Furthermore, it is noted by Keating (2000) that point estimates within an AVAR model selected with the Akaike information criterion are generally of comparable size to those obtained from VAR. Given that VAR is nested within the broader AVAR specification, AVAR offers a flexible method to address the issue of obtaining large numbers of insignificant coefficients. We therefore employ the AVAR model as a first layer of robustness to examine Granger causality between the variables of interest in our study.

As a third contribution, we explicitly recognise that in analysing the expanded database using AVAR, a multiplicity of testing is performed that introduces *multiple comparisons bias,* which we control using a generalised Holm correction method (Romano, Shaikh and Wolf, 2010). The bias arises when performing multiple hypothesis tests simultaneously, which leads to the non-negligible likelihood of identifying statistically significant results by pure chance alone, rather than on the basis of true statistical relationships. Without controlling for multiple comparisons bias, the probability of rejecting true hypotheses, i.e. making erroneous *false discoveries*, is increased. Addressing the bias is important as it calls into question, and potentially undermines, findings and conclusions presented at the conventional significance levels (i.e. 1%, 5% and 10%). To highlight the issue, results are first considered at the conventional significance levels and then the analysis is revisited with the generalised Holm correction. The analysis is in the spirit of Cummins (2013a, 2013b).

The remainder of the paper is organised as follows. Section 2 describes the data set used in the study and in particular the range of green equity indices considered. Section 3 presents the main findings of the price discovery analysis, reporting the Granger causal relationships between markets. The exact specification of the AVAR model is described in this section. Section 4 sets out the scale of the multiple comparisons problem inherent in the testing, while revisiting the empirical results in light of this. Section 5 concludes.

2 Data Description

For the price discovery analysis presented later, daily prices over the period 2 June 2008 - 1 May 2013 are used. The data is grouped into three categories: green equity indices, mainstream equity market indices and commodity markets. The green indices span global, regional and sectoral classifications and so permits a more in-depth price discovery analysis relative to previous literature. The green equity indices are drawn from the following prominent index series: Bloomberg New Energy Finance Clean Energy Indices; FTSE Environmental Markets Indices; and Wilderhill Indices. The global indices considered include the Wilderhill New Energy Global Innovation (NEX) index and the FTSE Environmental Opportunities Renewable and Alternative Energy index. The NEX is comprised of companies worldwide whose innovative technologies and services focus on generation and use of cleaner energy, conservation and efficiency, and advancing renewable energy generally. Included are companies whose lower-carbon approaches are relevant to climate change, and whose technologies help reduce emissions relative to traditional fossil fuel use. The FTSE EO Renewable and Alternative Energy index comprises all the companies in the Renewable and Alternative Energy subcategory of the FTSE Environmental Opportunities all-share index that meet the defined criteria for inclusion in this subcategory. In terms of regional indices, we focus on the Bloomberg Europe, Middle East & Africa Clean Energy index, which tracks clean energy companies domiciled in Europe, the Middle East and Africa. As we are particularly interested in examining relationships with the emissions markets and particularly emissions prices linked to the EU Emissions Trading Scheme, we therefore choose this regional index as it includes Europe within its geographical coverage. Finally, in terms of sectoral indices, we choose to include the clean technology FTSE ET50 index, which comprises the 50 largest pure play environmental technology companies globally, by full market capitalisation.

A suite of mainstream equity market indices is used to analyse the price transmission between green stocks and the broader stock markets. The FTSE 100 index is used to capture UK stock market activity, one of the key stock markets in Europe. In addition to this, the FTSE Global Small Cap and NYSE Archa Technology indices are considered. The Archa is an index purely focused on technology and comprises 100 companies listed on leading stock exchanges from industries including computer hardware, software, semiconductors, telecommunications, data storage and processing, electronics and biotechnology. The objective of the index is to provide a benchmark for measuring the performance of companies using technology innovation. It only includes companies where technology innovation is at the core of their business, therefore it is a useful index comparison against green economy companies who are using green innovation technology. The FTSE Global Small Cap index tracks small cap company stocks outside of the FTSE 350. It represents approximately 2% of the UK market capitalisation. Given that many of the green energy companies are considered small cap stocks, this index has been included to provide a more accurate comparative analysis to the green indices, particularly in the European region.

Oil, natural gas and carbon emissions are included in the mix of commodity markets data, where the objective is to investigate the direct relationship between the prices of these commodities and green company stock. Henriques and Sadorsky (2008), through referencing a range of authors, identify that there is a statistically significant relationship between oil and stock prices. The natural assumption is that the impact of rising oil prices on the stock prices of green economy companies would be positive, as it would encourage substitution of oil by clean energy. Our study will analyse if oil prices over the past five years have maintained this Granger causal effect on green stock prices. The prompt futures price for Brent crude oil is used, representing the key global benchmark for crude oil with some 70% of all international trade being priced off Brent, either directly or indirectly (Fattouh, 2011). Futures contract prices for Brent oil have been obtained from the Intercontinental Exchange (ICE). European natural gas prices are also included in our study, motivated by the recognition that natural gas is considered to be the transition fossil fuel to a low carbon economy. As the most liquid natural gas market in Europe, the prices of prompt month futures on National Balance Point gas are used, obtained again from ICE. This inclusion of natural gas extends the existing literature that has considered only oil to date.

For the emissions markets, the European Union Emissions Trading Scheme (EU ETS) is considered as it is the largest and most active emissions market in the world. The EU

ETS is the cornerstone of the European Union's policy to combat climate change, and has been since 2005. The EU ETS covers more than 11,000 power stations and industrial plants in 31 countries, as well as European airlines that operate within the EU jurisdiction. To track the price of carbon, two EU ETS permit types will be used: the primary European Union Allowances (EUA) compliance unit and the offsetting Certified Emission Reductions (CER) unit linked to the global Clean Development Mechanism (CDM). The inclusion of CER prices extends the previous literature, such as Kumar et al. (2012). The motivation for this is centred on the fact that CERs are awarded against projects funded and developed under the CDM as set out under the Kyoto protocol. As the CDM encourages private investment from developed nations in renewable energy and clean technology projects in developing nations, the CER prices are included here as a direct measure of this activity as it would be expected that some of the constituent companies within the green equity indices considered would be involved in the CDM markets. Price data for these units are obtained from ICE, the main trading platform for EU ETS emissions trading in Europe. For both the EUA and CER price data, the futures contracts with expiry of December 2012 are used, with both contracts rolled into the December 2013 expiry contract for the latter trade dates in December 2012 and the months spanning 2013 in our sample period. With a sample period from 2 June 2008 to 1 May 2013, the vast majority of Phase II of the EU ETS is covered in our study.

3 Methodology and Empirical Analysis

The dynamic relationships within green equity markets and between the broader equity and commodity markets are analysed through the use of Granger causality testing under an asymmetric vector autoregression (AVAR) model specification, which offers robustness over the conventional symmetric VAR model. Keating (2000) proposes this flexible methodology, which allows for asymmetry in the specification of the vector autoregression model. Within the AVAR model, each equation of the system contains the same variables, ensuring that parameter estimates are both consistent and efficient, but the lags of the variables are allowed to potentially differ. Keating (2000) notes that parameter estimates from AVAR models generally have smaller standard errors. Furthermore, it is noted by Keating (2000) that point estimates within an AVAR model selected with the Akaike information criterion are generally of comparable size to those obtained from VAR. Given that VAR is nested within the broader AVAR framework, AVAR offers a flexible method to address the problem with conventional VAR models whereby large numbers of insignificant coefficients are often obtained. We therefore employ the AVAR model in our study as a more robust approach to examine Granger causality between the variables of interest where the overall purpose of the price discovery analysis is to ascertain if the broader equity markets, along with the oil, natural gas and carbon markets, have an influence on the stock prices of green economy companies.

Variable	AVAR Lag Selection
NEX Index	1
FTSE EO Renewable & Alternative Energy Index	1
Bloomberg Europe, Middle East & Africa Clean Energy Index	2
FTSE ET50 Index	2
FTSE100 Index	2
FTSE Global Small Cap Index	1
NYSE Archa Technology Index	1
Brent Oil Prompt Futures	1
NBP Gas Prompt Futures	1
EUA Futures	2
CER Futures	1

Table 1: Asymmetric Vector Autoregression Model Specification

The AVAR framework in this empirical study involves eleven variables in total spanning the green equity indices, broader equity indices and commodities set out in the previous section, with a sample size of 1,238 daily price observations. As per Keating (2000), for a system of N variables and lags in the range 1 to M there are in total M^N possible AVAR specifications. Keating (2000) proposes that the optimal AVAR specification should be chosen on the basis of some selection criterion, such as the usual information criteria. We use the Akaike information criterion (AIC) as per Keating (2000) on the basis that, as noted earlier, point estimates within an AVAR model selected with the Akaike information criterion are generally of comparable size to those obtained from VAR. Furthermore, in the context of the conventional symmetric VAR model, Gonzalo and Pitarakis (2002) provide evidence that the AIC is the preferred choice for lag length selection in a high-dimensional system, such as the one we examine. Although the AIC is commonly known to overfit, the asymptotic probability of overfitting is an exponentially decreasing function of the system dimension. Furthermore, Gonzalo and Pitarakis (2002) point to a weakness with the Bayesian information criterion (BIC) and Hannan-Quinn criterion (HQC) tests in that they are likely not to move away from the lowest possible lag order within a high-dimensional system and additionally the authors raise questions over the ability of general to specific approaches to pick lag lengths other than those near the maximum lag selected for the testing. For our high-dimensional eleven-variable system the AIC would select a lag order of one in the case of a symmetric VAR model. Given this, and to utilise the flexibility that the AVAR framework offers, we select a maximum lag order of two to test. This therefore results in $2^{11} = 2,048$ alternative AVAR specifications. Using AIC we find the optimal AVAR specification and the resulting lags of the individual variables are set out in Table 1.

With the AVAR model optimally specified, we proceed with the Granger causality testing to establish if there is a causal link between the variables under consideration. Granger causality of course is a specific econometric concept and thus requires that a distinction be drawn between *true* causality and indeed other forms of causality. For the purposes of the exposition to follow, we will use the terms "Granger causality" and "causality" interchangeably in the understanding that we are always referring to Granger causality.[1] In general terms, VAR models and by extension AVAR models may of course be subject to omitted variable bias. As we extend the equity and commodity market dataset relative to previous studies, the potential for omitted variable bias in our analysis of the green equity markets is mitigated to a degree. However, in extending the database as we do, we inherently increase the amount of simultaneous hypothesis tests to be performed within the statistical framework, increasing multiple comparisons bias, i.e. the non-negligible likelihood of identifying statistically significant results by pure chance alone, rather than on the basis of true statistical relationships. So rather than being forced into making a subjective trade off between addressing omitted variable bias and multiple comparisons bias, we use a generalised multiple hypothesis testing technique, referred to as the generalised Holm correction, to formally control for multiple comparisons bias. We defer the discussion of the generalised Holm correction to Section 4 and so first present results at the conventional 1% and 5% statistical significance levels. Tables 2-3 present a summary of the Granger causality testing results. Only the significant results are presented to conserve on space given that there are 121 Granger causality tests in total in our system.

Results are broken down into the categories of (i) mainstream equity indices, (ii) green equity indices and (iii) commodities based on the leading causal variable in an identified causal relationship. To conserve on space, the estimated equations of the AVAR model are not presented but, unlike many vector autoregression studies presented in the literature, the results of the associated residual diagnostic testing are provided in Appendix A.[2] Before discussing the results of the Granger causality testing, it is necessary to briefly comment on the diagnostic tests, which show that based on multivariate tests the system residuals generally suffer from autocorrelation and heteroskedasticity effects and contravene the assumption of normality. On a univariate basis, the residual series from each equation in the AVAR system again generally show evidence of heteroskedasticity and non-normality but autocorrelation does not appear to be statistically significant in most cases. So given these residual biases some caution needs to be sounded around the resulting Granger causality testing. However, compared to the symmetric VAR(1) model, the test statistics all lead to much improved test statistics and hence higher p-values.

From the results of the Granger causality testing, it is first noted that the broad equity market indices, i.e. FTSE 100 and FTSE Global Small Cap, show evidence of having a causal effect on all of the green equity indices. As might be expected, there is very limited evidence of causality in the opposite direction, where we only see a causal influence on the

[1] We thank an anonymous reviewer for pointing out this subtlety.

[2] All unreported results are of course available from the authors upon request.

FTSE 100 from the regional Bloomberg Europe, Middle East & Africa Clean index and the sectoral FTSE ET50 index. Given that the FTSE 100 is a key stock index in Europe, its influence on green stocks is perhaps unsurprising. The FTSE Global Small Cap index was included in the dataset on the basis that many of the green energy companies are considered small cap stocks and so this index may provide a more accurate comparative analysis for the green indices. At least at conventional significance levels, we find evidence that this index of small cap companies does indeed exert a causal influence on green stocks; we will however return to this point later, subsequent to correcting for multiple comparisons bias. In terms of interactions within the green equity markets, we find evidence that the sectoral FTSE ET50 index has a Granger causal effect on the global FTSE EO Renewable and Alternative Energy index and the regional Bloomberg Europe, Middle East and Africa Clean Energy index. This price transmission provides modest evidence that the global green economy is becoming ever more integrated.

In terms of commodity market interactions, we see that NBP gas has a causal effect on all of the green equity indices. Henriques and Sadorsky (2008) and Kumar et al. (2012) do not include gas prices in their respective studies. The inclusion of gas in this study demonstrates that this commodity plays a more important role that oil. One explanation of this effect could be that a high proportion of the global green indices include renewable energy companies which supply power generators with cleaner generation options such as wind, solar and hydro. For power generation there has been an increase in gas use and opportunities for fuel switching are predominately from coal to gas, therefore gas as the transition fuel to a low carbon economy plays a key role in generation mix decisions. This in turn drives decisions on capital investment and also whether renewable energy will become part of a power generator portfolio. This may partly explain the greater influence of gas prices relative to oil prices. Indeed, we find that Brent crude oil futures prices do not have a Granger causal effect on the prices of the green indices. This finding is contrary to Henriques and Sadorsky (2008) and Kumar et al (2012), who both concluded that past oil prices explained movements in clean energy stocks. However, the period of observation for both datasets in these studies only goes to 2008, when oil prices were substantially higher. With the emergence of the credit crisis, oil prices collapsed from the highs of over $140/barrel in 2008 to below $40/barrel in early 2009, after which time prices have gradually increased but are still far off these 2008 levels.

Interesting as well is the observation that EUA and CER futures prices do not have a causal effect on any of the green economy indices, or indeed any of the other commodities. This is similar to the findings of Kumar et al (2012). The prices of emissions permits currently being commanded in the European emissions markets are considered by many to be excessively low to change the value proposition of a green product and make it competitive against fossil fuel alternatives. This price depression has resulted from an oversupply of units in the market due to excessive allocations in Phase I and II (Neuhoff et al., 2012), compounded by reduced demand due to the economic downturn. Therefore, the market is

Granger Causality	F-stat	p-value
Mainstream Equity Indices		
FTSE 100==>Bloomberg Europe, Middle East & Africa Clean Energy	12.652	0.0000***,†
FTSE 100==>EUA	3.436	0.0325**
FTSE 100==>FTSE EO Renewable & Alternative Energy	12.856	0.0000***,†
FTSE 100==>FTSE ET50	8.974	0.0001***,†
FTSE 100==>FTSE Global Small Cap	3.507	0.0303**
FTSE 100==>Nex	9.755	0.0001***,†
FTSE Global Small Cap==>Bloomberg Europe, Middle East & Africa Clean Energy	7.115	0.0077***
FTSE Global Small Cap==>Brent	16.044	0.0001***,†
FTSE Global Small Cap==>EUA	4.231	0.0399**
FTSE Global Small Cap==>FTSE 100	11.140	0.0009***,†
FTSE Global Small Cap==>FTSE EO Renewable & Alternative Energy	5.164	0.0232**
FTSE Global Small Cap ==>FTSE ET50	6.112	0.0136**
FTSE Global Small Cap ==>Nex	4.282	0.0387**
NYSE Archa Tech==>FTSE 100	6.847	0.0090***
NYSE Archa Tech==>FTSE EO Renewable & Alternative Energy	4.686	0.0306**
NYSE Archa Tech==>NYSE Archa Tech	4.276	0.0389**

The symbol "==>" is used to represent the direction of Granger causality. *** and ** denote significance at the 1% and 5% levels respectively. † denotes significance under the robust generalised Holm correction for multiple comparisons bias.

Table 2: Granger Causality Results

currently not functioning efficiently and with an ineffective carbon price, causal links with the share prices of green economy companies are not evident. To address the oversupply issue, the EU has proposed a short-term fix called 'backloading', whereby some of the due allocations of permits by member states to their industries would be postponed until later in the current phase, i.e. Phase II, of the scheme, which runs to 2020. The EU Parliament as of the end of 2013 has approved this proposal. The effectiveness the EU Emissions Trading Scheme may improve but currently the price is well below that necessary to convince power generators to carry out fuel switching or invest in low carbon technologies. Any causal relationships, which according to theoretical norms should appear, are not evidenced in our analysis.

Granger Causality	F-stat	p-value
Green Equity Indices		
Bloomberg Europe, Middle East & Africa Clean Energy==>Brent	10.487	0.0000***,†
Bloomberg Europe, Middle East & Africa Clean Energy==>FTSE 100	7.191	0.0008***,†
FTSE EO Renewable & Alternative Energy==>Brent	4.611	0.0320**
FTSE ET50==>Bloomberg Europe, Middle East & Africa Clean Energy	9.256	0.0001***,†
FTSE ET50==>FTSE 100	4.191	0.0154**
FTSE ET50==>FTSE EO Renewable & Alternative Energy	4.823	0.0082***
Commodities		
EUA==>CER	7.490	0.0006***,†
NBP Gas==>Bloomberg Europe, Middle East & Africa Clean Energy	5.495	0.0192**
NBP Gas==>Brent	3.979	0.0463**
NBP Gas==>FTSE 100	4.521	0.0337**
NBP Gas==>FTSE EO Renewable & Alternative Energy	4.317	0.0379**
NBP Gas ==>FTSE ET50	5.931	0.0150**
NBP Gas==>FTSE Global Small Cap	7.993	0.0048***,†
NBP Gas==>Nex	8.275	0.0041***,†
NBP Gas==>NYSE Archa Tech	6.727	0.0096***

The symbol "==>" is used to represent the direction of Granger causality. *** and ** denote significance at the 1% and 5% levels respectively. † denotes significance under the robust generalised Holm correction for multiple comparisons bias.

Table 3: Granger Causality Results (contd.)

4 Correction for Multiple Comparisons Bias

The previous analysis sets out a range of interactions between the green equity markets and the broader equity and commodity markets; all identified at the conventional 1% and 5% statistical significance levels. However, with eleven variables of interest, the Granger causality testing conducted has an important limitation. The testing framework involves 121 simultaneous pairwise Granger causality hypothesis tests, and when coupled with the univariate and multivariate diagnostic tests, leads to a total of 158 hypotheses of interest. This introduces the well-established *multiple comparisons bias*, whereby under naive analysis the identification of significant results may occur by pure chance alone, i.e. false discoveries may be made (Romano and Wolf 2007, 2010; Romano et al., 2010). A key contribution of this paper is that we add a further layer of robustness to our robust AVAR-based testing by means of explicitly correcting for this multiple comparisons bias, thus ensuring that we do not make conclusions and findings that are potentially based on spurious false discoveries.

By way of motivation first, take for instance Henriques and Sardorsky (2008) and if we isolate just the Granger causality testing, it is noted that the authors examine 16 pairwise relationships. An immediate way to control for multiple comparisons bias here would have been to apply a Bonferroni correction (Romano, Shaikh and Wolf, 2009). The Bonferroni correction is designed to cap the probability that *one or more* false discoveries is identified across the family of tests at a specified level α by using for each hypothesis test a *per comparison* cut-off value equal to α divided by the number of hypothesis tests s, i.e. a causal relationship is deemed significant only if its associated p-value is less than or equal to α/s. So, to keep the probability of identifying one or more false discoveries among the multiplicity of Granger causality tests at 5% in the Henriques and Sardorsky (2008) study, only results with a p-value less than or equal to $5\%/16 = 0.3125\%$ would be deemed statistically significant. Likewise, Kumar et al. (2012) perform 75 pairwise Granger causality tests. Applying the Bonferroni correction again such that the probability of identifying one or more false discoveries is limited to α would require a *per comparison* cut-off value of $5\%/75 = 0.0667\%$, so only results with a p-value less than or equal to this level would be deemed significant.

The above Bonferroni correction examples highlight the multiple comparison problem and motivate the need to correct for this source of bias in order to ensure robustness in the economic conclusions drawn. However, the Bonferroni correction is criticised for the fact that it is a highly conservative multiple hypothesis testing technique. This can be seen by the low *per comparison* cut-off values calculated above, which make it difficult to reject a null hypothesis at all. However, recent literature proposes *generalised* multiple hypothesis testing techniques that relax this conservatism and allow for greater power. This section introduces one such generalised technique that will be used to control for the multiple comparisons problem inherent in our testing. The issue again with multiple hypothesis testing (MHT) is that the probability of false discoveries, i.e. the rejection of true null hypotheses by chance alone, is often significant. Romano, Wolf and Shaikh (2010) provide an excellent summary of the issues and the literature. We use a correction technique based on the *generalised familywise error rate* (k-FWER), which is defined to be the probability of obtaining a given $k \geq 1$ *or more* false discoveries from a suite of hypothesis tests. Controlling the k-FWER involves setting a significance level α and requiring that k-FWER $\leq \alpha$. The correction method we use is that of Lehmann and Romano (2005), who propose a recursive stepdown method that generalises the method of Holm (1979) by means of defining the following set of cut-off values for comparison against the hypothesis test p-values when ordered from the most significant (lowest p-value) to the least significant (highest p-value):

$$\alpha_{(i)} \equiv \begin{cases} \frac{k\alpha}{s}, & i \leq k \\ \frac{k\alpha}{s+k-i}, & i > k \end{cases},$$

where $i = 1, \ldots, s$ and s is the total number of hypothesis tests performed simultaneously. In our case, $s = 158$, which includes the Granger causality and residual diagnostic testing. This procedure has the advantage of being robust to the dependence structure of the hypothesis tests, with the additional advantage of being a superior stepwise procedure (Romano, Wolf and Shaikh, 2010). To ensure tight control over the number of false discoveries while at the same time offering power to the testing, k is chosen for this study to ensure that no more than 5% of the tests represent false discoveries. Hence, based on a population of $s = 158$ hypothesis tests, k is set equal to $\lceil 158 \times 5\% \rceil = 8$. The significance level α chosen is 10%, such that the implementation of the generalised Holm procedure ensures that the probability of eight or more false discoveries is capped at 10%.

Returning to the results in Tables 2-3, it can be seen that those tests that are significant after the generalised Holm correction have been highlighted. When accounting for the multiple comparisons bias explicitly as set out above, it can be seen that much fewer statistically significant results are identified relative to the conventional 1% and 5% significance levels. Among these results, it can be seen that the causal influence of the FTSE 100 on all of the green equity indices holds. In contrast though, the causal influence of the FTSE Small Cap index that was evidenced at conventional significance levels fails to make it through the robust generalised Holm correction. Interestingly, the link between the NBP gas and the green sector, although less extensive, does hold; with NBP gas showing evidence of a causal effect on the global NEX index. Between the green equity indices, we found even more modest evidence of interactions. Subsequent to the application of the generalised Holm correction we find that the sectoral FTSE ET50 has a causal relationship with the only regional Europe, Middle East and Africa Clean Energy index.

In conclusion, what appear to be some anomalies in the results must be discussed. At conventional significance levels, the findings suggest that the FTSE EO Renewable and Alternative Energy index and the Bloomberg Europe, Middle East and Africa Clean Energy index have a causal influence on Brent. There is no apparent economic rationale for this, particularly as we do not see oil prices having an effect on green stocks. The former observation falls out after applying the generalised Holm correction. The latter observation however does hold. This may be due to the fact that we are using a *generalised* correction technique, which we have set up to control for the probability of eight or more false discoveries. The generalised nature of the correction technique is such that it gives the overall testing framework more power but it does open up the prospect of some false discoveries slipping through the robustness filter. It could be rightly argued that the observation that the Bloomberg Europe, Middle East and Africa Clean Energy index influences Brent oil is most likely a false discovery. Notwithstanding this, the analysis presented in this paper serves to highlight the importance of controlling for the multiple comparisons problem within large scale hypothesis testing applications. Indeed, without the generalised Holm procedure, it would have been naively concluded that, at the 5% significance level, 31 of the 121 pairwise Granger causality tests were statistically significant (a rejection rate of ∼26%), rather than the 12 deemed significant post-correction (a rejection rate of only∼10%). This underscores the importance of applying multiple hypothesis testing procedures. The use of the multiple hypothesis testing procedure in this study therefore provides an additional layer of robustness to the already robust AVAR model implementation.

5 Conclusion

A price discovery analysis is performed to determine interactions within the green equity sector, in addition to interactions among the broader equity markets and the commodity markets. Three pivotal contributions are made. Our first contribution extends existing literature with an expanded database of green equity indices, broader equity market indices and commodities relative to previous literature. The suite of green equity indices includes global, regional and sectoral indices drawn from the Bloomberg New Energy Finance Clean Energy Index, FTSE Environmental Markets Index and Wilderhill Index series. This extended database allows for greater depth in determining general global, regional and sectoral price transmission. The commodities database is extended by means of including natural gas prices, recognising that natural gas is seen as the transition fossil fuel to a low carbon economy, and Certified Emissions Reduction emissions prices as a measure of Clean Development Mechanism (CDM) activity, recognising that some of the constituent companies within the green economy would likely be involved in the CDM markets. Our second contribution provides a first layer of robustness to our testing. Addressing the limitation of conventional symmetric VAR that leads to the estimation of a large number of insignificant coefficients, we use the asymmetric vector autogression (AVAR) model of Keating (2000). Within an AVAR, each equation of the model system contains the same variables, ensuring that parameter estimates are both consistent and efficient, but the lags of the variables are allowed to potentially differ. Keating (2000) notes that parameter estimates from AVAR models generally have smaller standard errors and that point estimates selected with the Akaike information criterion are generally of comparable size to those obtained from VAR. Our third contribution corrects for the multiple comparisons bias inherent in the multiplicity of testing under the AVAR model. We control for this source of bias by means of using a generalised Holm correction (Romano, Shaikh and Wolf, 2010). Without controlling for multiple comparisons bias, the probability of rejecting true hypotheses, i.e. making erroneous *false discoveries*, is increased.

At conventional statistical significance levels, we find that the FTSE 100 and FTSE Global Small Cap indices have a causal effect on all of the green equity indices, with limited evidence of causality in the opposite direction. In terms of interactions within the green equity markets, we find evidence that the sectoral FTSE ET50 index has a Granger causal effect on the global FTSE EO Renewable and Alternative Energy index and the regional Bloomberg Europe, Middle East and Africa Clean Energy index. This price transmission provides modest evidence that the global green economy is becoming ever more integrated. NBP gas is shown to have a causal effect on all of the green equity indices, whereas we find no such evidence for Brent oil. The former observation may reflect the increasing role of gas as the transition fuel to a low carbon economy, playing a key role in decisions on power generation mix and associated capital investment. This may partly explain the greater influence of gas prices relative to oil prices. Finally, we find no evidence that EUA or CER emissions prices have a causal effect on green stocks, consistent with previous findings and likely reflecting the excessively low prices being commanded for compliance permits in the European emissions markets.

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A Residual Diagnostic Tests

This appendix presents the autocorrelation, ARCH and normality tests on the residuals of the asymmetric vector autoregression (AVAR) model implemented in Section 3.

A.1 Residual Autocorrelation Testing

		Univariate Autocorrelaton (Ljung-Box) Test	
Equation	Dep Variable	Test Statistic (3 Lags)	p-value
1	NEX Index	0.19	0.9791
2	FTSE EO Renewable & Alternative Energy Index	1.40	0.7047
3	Bloomberg Europe, Middle East & Africa Clean Energy Index	2.33	0.5065
4	FTSE ET50 Index	0.36	0.9475
5	FTSE100 Index	5.91	0.1163
6	FTSE Global Small Cap Index	0.05	0.9975
7	NYSE Archa Technology Index	2.70	0.4409
8	Brent Oil Prompt Futures	6.87	0.0761
9	NBP Gas Prompt Futures	10.79	0.0129**
10	EUA Futures	2.99	0.3934
11	CER Futures	3.48	0.3237

Multivariate Autocorrelation (Ljung-Box) Test	
Test Statistic (3 Lags)	p-value
258.21	0.0026***,†

The symbol "==>" is used to represent the direction of Granger causality. *** and ** denote significance at the 1% and 5% levels respectively. † denotes significance under the robust generalised Holm correction for multiple comparisons bias.

Table 4: Residual Autocorrelation

A.2 Residual Autoregressive Conditional Hetroskedasticity (ARCH) Testing

		Univariate ARCH Test	
Equation	Dep Variable	Test Statistic (3 Lags)	p-value
1	NEX Index	169.18	0.0000***,†
2	FTSE EO Renewable & Alternative Energy Index	175.98	0.0000***,†
3	Bloomberg Europe, Middle East & Africa Clean Energy Index	120.44	0.0000***,†
4	FTSE ET50 Index	205.41	0.0000***,†
5	FTSE100 Index	142.96	0.0000***,†
6	FTSE Global Small Cap Index	167.43	0.0000***,†
7	NYSE Archa Technology Index	194.31	0.0000***,†
8	Brent Oil Prompt Futures	148.09	0.0000***,†
9	NBP Gas Prompt Futures	1.47	0.6890
10	EUA Futures	9.93	0.0191**
11	CER Futures	143.69	0.0000***,†

Multivariate ARCH-LM Test		
	Test Statistic (3 Lags)	p-value
	25578.26	0.0000***,†

The symbol "==>" is used to represent the direction of Granger causality. *** and ** denote significance at the 1% and 5% levels respectively. † denotes significance under the robust generalised Holm correction for multiple comparisons bias.

Table 5: Residual Heteroskedasticity

A.3 Residual Normality Testing

		Univariate Normality Test	
Equation	Dep Variable	Test Statistic	p-value
1	NEX Index	930.81	0.0000***,†
2	FTSE EO Renewable & Alternative Energy Index	956.31	0.0000***,†
3	Bloomberg Europe, Middle East & Africa Clean Energy Index	685.30	0.0000***,†
4	FTSE ET50 Index	1217.65	0.0000***,†
5	FTSE100 Index	943.07	0.0000***,†
6	FTSE Global Small Cap Index	928.00	0.0000***,†
7	NYSE Archa Technology Index	853.75	0.0000***,†
8	Brent Oil Prompt Futures	547.18	0.0000***,†
9	NBP Gas Prompt Futures	41995.09	0.0000***,†
10	EUA Futures	31553.58	0.0000***,†
11	CER Futures	13407.41	0.0000***,†

Multivariate Normality Test		
	Test Statistic	p-value
Asymptotic	25578.26	0.0000***,†
Omnibus Doornik-Hansen	8146.31	0.0000***,†

The symbol “==>” is used to represent the direction of Granger causality. *** and ** denote significance at the 1% and 5% levels respectively. † denotes significance under the robust generalised Holm correction for multiple comparisons bias.

Table 6: Residual Normality

***Highlights**

Price Discovery Analysis of Green Equity Indices using Robust Asymmetric Vector Autoregression

September 30, 2014

Paper Highlights

- Green equity indices considered spanning global, regional and sectoral.
- Use of robust asymmetric vector autoregression model.
- Evidence of wide range of interactions within and across markets.
- Broad equity indices and NBP natural gas idenified as main causal influences.
- Recognition of multiple comparisons bias and application of correction techniques.