



Rita Mafalda Dionísio de Sousa

Mestrado em Economia e Política da Energia e do Ambiente
Licenciatura em Economia

Carbon Prices

Dynamic analysis of European and Californian markets

Dissertação para obtenção do Grau de Doutor em
Alterações Climáticas e Políticas de Desenvolvimento Sustentável

Orientador: Professor Doutor Rui Santos,
Professor Associado,
Universidade Nova de Lisboa

Co-Orientador: Professor Doutor Luís Aguiar-Conraria,
Professor Associado com Agregação
Universidade do Minho

Júri:

Presidente: Prof^a. Doutora Maria Paula Pires dos Santos Diogo
Arguentes: Prof. Doutor Miguel Pedro Brito St. Aubyn
Prof. Doutor Tiago Morais Delgado Domingos

Vogais: Prof. Doutora Maria Isabel Rebelo Teixeira Soares
Prof. Doutora Maria Júlia Fonseca de Seixas
Prof. Doutor Rui Jorge Fernandes Ferreira dos Santos
Prof. Doutor Luís Francisco Gomes Dias de Aguiar Conraria



FACULDADE DE
CIÊNCIAS E TECNOLOGIA
UNIVERSIDADE NOVA DE LISBOA

Maio 2014

Copyright

“Carbon Prices - Dynamic analysis of European and Californian Markets”

Rita Mafalda Dionísio de Sousa

Faculdade de Ciências e Tecnologia e a Universidade Nova de Lisboa

A Faculdade de Ciências e Tecnologia e a Universidade Nova de Lisboa têm o direito, perpétuo e sem limites geográficos, de arquivar e publicar esta dissertação através de exemplares impressos reproduzidos em papel ou de forma digital, ou por qualquer outro meio conhecido ou que venha a ser inventado, e de a divulgar através de repositórios científicos e de admitir a sua cópia e distribuição com objectivos educacionais ou de investigação, não comerciais, desde que seja dado crédito ao autor e editor.

Faculdade de Ciências e Tecnologia, Universidade Nova de Lisboa, 05/05/2014



Rita Mafalda Dionísio de Sousa

Dedicatory

For Júlia

Acknowledgments

The work presented in this thesis would not be possible without the help of the following people, to whom I am truly grateful.

My supervisors, Professor Rui Santos and Professor Luís Aguiar Conraria. Professor Rui Santos for all the help and support in carrying out the work, for his constructive criticism, and for all the help in meeting the imposed deadlines. I also thank Professor Luís Aguiar Conraria who was the technical pillar of this thesis, sharing knowledge and demonstrating seemingly endless doses of motivation.

Pedro M. Barata, for inspiring the theme I have chosen, and being my mentor. Someone who, despite the short time he has, was available for sharing very helpful comments. The affection he has on climate change issues contaminates all those around him, and I'm no exception.

Professor Isabel Soares, for her manifested interest and curiosity, being the first supporter and supervisor of my academic research on carbon prices.

Relatives, friends and colleagues who helped me when it seemed I had reached a dead end, supporting the revision of the text or making illuminating comments: Isabel Tarroso, Maria João Martins, Nuno Antunes, Ana Rovisco, Renato Rosa, Rui Ochôa, Cláudia Sousa and Professor M^a Joana Soares.

To Nelson Soares and Professor Cláudio Monteiro, at Smartwatt, for their enthusiasm at the start of my academic career and the backing when attending the PhD Lisbon classes.

Professors Jorge Pereira and Peças Lopes, at the Power Systems Unit of INESC Porto, for the support to the 1st year of PhD classes.

I also thank the School of Economics and Management at the University of Minho, for the logistic support, providing me with a workplace, hardware and software.

The promoters of the Doctoral Program in Climate Change and Sustainable Development Policies, for the opportunity to attend advanced studies in this area of reference, in Portugal.

Globally, I thank the people and institutions that facilitated access to essential data to my work: Euronatura, Kate Jazgara at The ICE - IntercontinentalExchange, the European Energy Exchange EEX, the Climate Policy Initiative, the European Climate Assessment and Dataset, and Michelle Breckner at the Western Regional Climate Center US.

Finally, I thank my Mother, for the relentless support with Júlia and everything else. Without her it would not have been possible to complete this work. And that sums it up.

My Father, another huge support, irrefutable proof that many miles do not necessarily make great distances.

Júlia, for the eternal smiles she was born with, and with which she presents me with every day. And Marco, for the Art that he puts in my life every day. It is what gives everything a meaning.

Thank you all.

Resumo

Os mercados de carbono existem para promover a redução de emissões de gases com efeito de estufa onde esta é mais custo-eficiente. O preço do bem transaccionável, o carbono (CO_2 equivalente), é, por isso, uma variável chave nas decisões de gestão da produção e do risco nos mercados associados a actividades ligadas à queima de combustíveis fósseis, como a produção de electricidade.

Este trabalho pretende melhorar a análise da dinâmica dos preços de carbono, considerando a possibilidade de existência de efeitos multidireccionais entre preços de carbono, da energia (final e primária), de licenças de offsets, e a performance da economia, em várias frequências. As duas principais perguntas de investigação são: (i) o que orienta os preços de carbono? (ii) em que preços as variações são consequência dos preços de carbono? Utilizaram-se duas metodologias complementares: (a) um modelo vector auto-regressivo (de uso comum na macroeconomia e mercados financeiros, mas pouco aplicado à relação energia-carbono) que permite a análise de causalidade e de impulso-resposta de preços diários; e (b) uma inovadora análise multivariada de wavelets, que permite perceber a relação e causalidade existente entre as variáveis nas dimensões tempo e frequência, nomeadamente em ciclos mais longos (4~8 e 8~20 meses), não captada em nenhuma análise prévia. Consideram-se como casos de estudo os mercados de carbono Europeu (EU ETS) e da Califórnia (AB32), sendo este o primeiro trabalho de investigação a apresentar a análise do mercado americano. A análise abrange o período de 2008 a 2013, e excluiu a fase I do EU ETS, para maior consistência da amostra.

Os resultados obtidos permitem sugerir que a economia e os preços da electricidade orientam o preço de carbono Europeu, enquanto na Califórnia o gás e o petróleo têm um papel mais relevante, havendo, portanto maior influência dos preços de energia final no mercado mais maduro. Também observamos que o preço das CERs não influencia o preço de carbono Europeu. Inversamente, este estudo apresenta pela primeira vez evidências de que os preços do carbono têm impactos no preço da electricidade em ciclos mais longos (8~20 meses) e no carvão em ciclos curtos, e com duração limitada aos primeiros dias. Sugere, portanto, que o mercado de emissões surte efeitos mais significativos em ciclos mais longos. Por fim, o preço de carbono Europeu também mostra influências nos preços das CERs. Os resultados obtidos são estatisticamente significativos e relevantes, e irão melhorar a qualidade na tomada de decisão das partes envolvidas nos mercados de energia e de carbono, poluidores e reguladores.

Palavras-chave: Preços de CO_2 , modelo VAR, análise multivariada de Wavelets, EU ETS, AB32.

Abstract

Carbon markets' goal is to promote the reduction of emissions of greenhouse gases where it is most cost-efficient. This makes the price of the tradable good – carbon dioxide equivalent (CO₂e) - a key variable in management and risk decisions, in markets related to activities connected with the burning of fossil fuels, such as power generation.

This work aims to improve the analysis of carbon prices' dynamics, considering the possibility of multidirectional effects between prices of CO₂e, energy (primary and final), offsets licenses and the economy performance, in various frequencies. The two main research questions are: (i) what drives carbon price variations? (ii) what variations do carbon prices drive? We used two complementary methodologies: (a) a vector autoregression model (of common use in macroeconomics and financial markets but not in carbon-energy relations), which allows the analysis of causality and of impulse-response functions of daily prices; and (b) an innovative multivariate wavelet analysis, which allows us to understand the relationship and causal link between the variables in the time and frequency dimensions, particularly in longer cycles (4~8 and 8~20 months), not perceived in previous studies. As case studies we considered the European (EU ETS) and California (AB32) carbon markets. This is the first research to present the analysis of the referred US market. The analysis covers the 2008-2013 period, intentionally excluding the EU ETS phase I, for greater consistency of results.

Results suggest that the economy and electricity drive the price of European carbon, while gas and oil have a greater role in California. So, there is a greater influence of final energy prices in the most mature market. We also observe that the price of CERs does not affect the European carbon price. On the other hand, this study shows for the first time that carbon prices have impacts on electricity prices over longer cycles (8~20 months) and in coal over short cycles (limited to the first days). It is suggested that the carbon market has more significant effects in longer cycles. The price of European carbon also has impact in CERs prices. The results are statistically significant and relevant, and will improve the quality of decision making of all parties involved in the energy and carbon markets - polluters and regulators included.

Keywords: Carbon Prices, VAR model, Multivariate wavelet analysis, EU ETS, AB32

CONTENTS

Index of Figures	xiii
Index of Tables	xv
Abbreviations	xvii
Variables	xix
Units	xix
1 Introduction.....	1
2 Methodology	13
2.1 The Vector Autoregression Model (VAR).....	13
2.1.1 Background on VAR models	13
2.1.2 Theory of a VAR model.....	15
2.2 Multivariate Wavelets Analysis	23
2.2.1 Background on wavelet analysis	23
2.2.2 Theory of multivariate wavelets	27
3 Dynamics of Carbon Prices.....	39
3.1 Introduction	39
3.2 Part I – Europe: EU ETS.....	47
3.2.1 EU ETS main features	47
3.2.2 Selected data.....	49
3.2.3 VAR analysis	54
3.2.4 Wavelets analysis	64
3.2.5 EU ETS synthesis of results.....	70
3.3 Part II – California: AB32	73
3.3.1 AB32 main features.....	73
3.3.2 Selected data.....	79
3.3.3 VAR analysis	83
3.3.4 Wavelets analysis	92
3.3.5 AB32 synthesis of results.....	96
4 Discussion.....	99
5 Final remarks and directions for further research	111
Bibliography	117

Appendix - data output and econometric tests	129
A European data	129
A.1 Econometric data tests.....	129
A.2 VAR Granger Causality/Block Exogeneity Wald Tests	130
A.3 Variance decomposition.....	131
A.4 VAR output	133
B California data.....	140
B.1 Econometric data tests.....	140
B.2 VAR Granger Causality/Block Exogeneity Wald Tests	141
B.3 Variance decomposition.....	142
B.4 VAR output	144

INDEX OF FIGURES

Figure 1 : Emission trading schemes around the World	5
Figure 2 : Sea surface temperatures averaged over the NINO3 area in the eastern Pacific.	23
Figure 3 : The Fourier transform of a time series	24
Figure 4 : Wavelet power spectrum of sea surface temperatures in the eastern Pacific.....	26
Figure 5 : The real part of a Morlet wavelet	31
Figure 6 : Phase relations between time series x and y	35
Figure 7 : EU carbon prices, 2008/2013.	50
Figure 8 : EU selected energy prices, 2008/2013.....	52
Figure 9 : EU prices - Granger causality tests	55
Figure 10 : Variance decomposition of carbon and electricity prices - EU	57
Figure 11 : CO ₂ price returns accumulated responses to impulses in other variables - EU	58
Figure 12 : Impulses in CO ₂ prices and accumulated responses of selected EU prices	60
Figure 13 : Other accumulated impulse-response functions of energy prices - EU.....	62
Figure 14 : Causality cycles between electricity and gas prices - EU	63
Figure 15 : Other causality cycles: the role of coal – EU	63
Figure 16 : Other causality cycles: the role of gas - EU	64
Figure 17 : EU prices - time-series plot and time-series wavelet power spectrum	65
Figure 18 : EU prices - wavelet coherence and phase-differences	67
Figure 19 : EU prices - partial wavelet coherence and partial phase-differences	69
Figure 20: California carbon prices, 2011/2013	80
Figure 21 : California selected energy prices, 2011/2013.....	82
Figure 22 : California prices - Granger causality tests	84
Figure 23 : Variance decomposition of carbon and electricity prices - CA	86
Figure 24 : CO ₂ price returns accumulated responses to impulses in other variables - CA	87
Figure 25 : Impulses in CO ₂ prices and accumulated responses of CA prices.	90
Figure 26 : Other accumulated impulse-response functions of energy prices - CA.....	91
Figure 27 : Other causality relations of CO ₂ - CA.....	91
Figure 28 : CA prices - time-series plot and time-series wavelet power spectrum	93
Figure 29 : CA prices - wavelet coherence and phase-differences	94
Figure 30 : CA prices - partial wavelet coherence and partial phase-differences.....	96

INDEX OF TABLES

Table 1 : Power generation in California, per source and geographic origin.....	76
Table 2 : Outline of obtained significant results of variables relationships with carbon price.	101

ABBREVIATIONS

AAU	assigned amount unit	GARCH	generalized autoregressive conditional heteroskedasticity
AB32	assembly bill 32	GDP	gross domestic product
ACV	auto covariance	GHG	greenhouse gas
AR	auto regression	ICE (The)	intercontinental exchange
AR5	assessment report 5	IPCC	intergovernmental panel on climate change
BBL	barrel	IRF	impulse response function
BTU	British thermal unit	JI	joint implementation
CARB	California air resources board	LR	likelihood ratio
CCA	California carbon allowance	MMBTU	million BTU
CDM	clean development mechanism	MWA	multivariate wavelet analysis
CDS	clean dark spread	NA2050	North America 2050
CER	certified emission reduction	NAS	national academies of sciences
CIF	Cost, insurance, freight	NO _x	mono-nitrogen oxides
CO ₂	carbon dioxide	OLS	ordinary least squares
CO ₂ e	CO ₂ equivalent	RAWS	remote automated weather stations
COI	cone of influence	RGGI	regional greenhouse gas initiative
CSS	clean spark spread	SO ₂	sulfur dioxide
CWT	continuous wavelet transform	STFT	short time Fourier transform
EC	European Commission	SVAR	structured VAR
EEX	European energy exchange	tCO ₂	tonne of CO ₂
EF	emission factor	UNFCCC	united nations framework convention on climate change
EIA	energy information administration	VAR	vector autoregression
ENSO	El Niño southern oscillation	VMA	vector moving average
EPA	US environmental protection agency	WCI	western climate initiative
EU ETS	European Union emissions trading scheme	Wh	Watt hour
EUA	European Union allowance	Whe	Watt hour equivalent

VARIABLES

EU ETS (prices)

CO ₂	1 EUA
CER	1 CER
ELE_b	baseload electricity price 1 MWh
ELE_p	peak electricity price 1 MWh
Coal	1 tonne coal
Gas	1 MMBTU
Econ or FTSE	economy performance index 1 unit

AB32 (prices)

CO ₂	1 CCA
ELE	electricity price 1 MWh
Gasoline	1 gallon
Coal	1 tonne coal
Gas	1 MMBTU
Oil	1 USbbl
Econ	economy performance index 1 unit

UNITS

Symbol Factor

G	Giga = 10 ⁹
M	Mega = 10 ⁶
k	Kilo = 10 ³
MM	Million = 10 ⁶
--	Trillion = 10 ¹² (short scale)

t Tonne = 10³ kg
= 10⁶ g

g gram

USbbl US barrel = 159 litres
gal 1 gallon = 3.78541 litres

1 INTRODUCTION

Global warming is a circumstance of our time coupled to activity of Humankind. Since the Industrial Revolution, the burning of fossil fuels has escalated, increasing the concentration of greenhouse gases (GHG) in the planet's atmosphere (IPCC 2007). The accumulation of those gases creates a greenhouse effect that keeps our planet temperature in an equilibrium. However, when GHG concentration is above ideal levels, global temperatures rise, causing changes in the Earth's climate.

The United Nations Framework Convention on Climate Change, UNFCCC (1992), in its article 1, n.2, p.3, defines anthropogenic climate change as “a change of climate which is attributed directly or indirectly to human activity that alters the composition of the global atmosphere and which is, in addition to natural climate variability, observed over comparable time periods”. Anthropogenic climate change has also become known as global warming. To support this definition, the Intergovernmental Panel on Climate Change (IPCC), the scientific body for the UNFCCC, gathered research supporting an increase in the average temperature of Earth's surface by 0.74C since the 19th century. If no action is taken, the IPCC forecasts a rise up to 1.4°C to 5.8°C above 1990 levels, by 2100 (Meehl and al 2007). This unfortunate prediction is recognised by major National Science Academies (NAS 2005, AAAS 2009, AGU 2013).

In its most recent report (Assessment Report 5 – AR5), the IPCC identifies a GHG emissions budget¹ of 840Gt. This carbon budget would allow the world to have a 50% chance of staying below 2°C of warming by 2100, above 1861-1880 levels (IPCC 2013). Current emission rates are at 10GtC per year and about 531GtC has already been used (IPCC 2013). So, without additional action, in 30 years the budget will have been used. With this knowledge, effects of global warming, such as melting glaciers and more frequent extreme weather events, that can already be felt in some parts of the globe, are estimated to worsen in the coming decades (EC 2013a). As an example, under a high emissions scenario, by 2050 the Arctic Ocean is expected to have no ice during the summer (IPCC 2013). In fact, the IPCC states that about 20-30% of plant and animal species is likely at higher risk of extinction if the global average temperature goes up by more than 1.5 to 2.5°C (IPCC 2007). In short, the IPCC points out consequences such as «agricultural yields expected to drop [...]; diseases [...] could spread to new areas in the world; millions of

¹ Carbon budget: cumulative greenhouse gas emissions over time.

people expected to be exposed to increase water stress; more intense weather-related disasters; and extinctions» UNFCCC (2007), p.1. Sectors such as agriculture, energy and tourism, very dependent on the level of temperature, precipitation and sea level, will, thus, be particularly affected by global warming (EC 2013a).

It is reasonable to say that climate change will globally have harmful effects on societies and the economic and natural systems in which they live.

In this context, the UNFCCC, created in 1992, has the goal of achieving the «stabilization of greenhouse gas concentrations in the atmosphere at a level that would prevent dangerous anthropogenic interference with the climate system. Such a level should be achieved within a time-frame sufficient to allow ecosystems to adapt naturally to climate change, to ensure that food production is not threatened and to enable economic development to proceed in a sustainable manner» (UNFCCC 1992), article 2, p.4. 195 countries ratified this overall global objective, promising to engage in mitigation actions, that is, actions that reduce net carbon emissions and limit long-term climate change (IPCC 2007). An important concept in climate change and carbon economics is “mitigation”, the act of decreasing future global warming.

With the mitigation purpose in mind, Governments have a very important role of engaging polluting companies and the society in reducing their emissions. There are essentially two policy instruments that help attain the desired goal: either command-and-control imposed regulations, or economic incentive instruments.

The first option, to enforce emission limits, is rather inflexible and does not provide an incentive for emitters to engage in further reductions beyond the imposed limit. Also, imposed regulations are known to be less efficient and less cost-effective than other options, for they rely on a precise definition of the conditions and quantities of emissions, which are uncertain to a certain point (Tietenberg and Lewis 2009).

Alternatively, as economic incentive instruments to control emissions we find taxes and cap-and-trade, although cap-and-trade includes a command and control feature regarding the pollution limit that must be defined. Both trading and taxes recognize a market failure stemming from a negative externality. Atmospheric pollution constitutes a negative externality because polluters do not compensate society for the damage they cause. “Climate change is the greatest market failure the world has ever seen” (Stern 2006). To address these climate externality costs, cap-and-trade bounds a “set amount” of emissions, while taxes work indirectly.

Emission taxes are defined in the form of a Pigouvian tax where the negative externality is internalized through a tax equal to the marginal social cost of pollution (Pigou 1924). Under typical

theoretical economic system conditions, such as perfect information, rational agents and no transaction costs, both tools, taxes and cap-and-trade, should reach a set amount of emission. They both put a price on carbon, thus consequently correcting the market failure. However, while cap-and-trade provide certainty on emission quantities, taxes, on the other hand, are only 'cost' certain (Helm 2005).

The idea of a cap-and-trade, or an emission market mechanism, was initially born in a study by Coase (1960) regarding property rights. Under certain conditions, by clearly defining property rights, and making them exchangeable, the market would give a value to those rights and allocate them to "their best use", as Tietenberg (2010) poses. After Coase, Crocker (1966) applies the concept to air pollution and Dales (1968) to water. Baumol and Oates (1971), p.42, corroborate the idea stating that "for any given vector of final outputs such prices can achieve a specified reduction in pollution levels at minimum cost to the economy". Greenhouse gases pollution are an example of Baumol and Oates idea, which only applies when all emissions have the same impact on the environment. In this case, GHGs have the same impact regardless of the location from where they are emitted.

In emission control policy, preference has been shown for emissions trading over the imposition of taxes. The main reason for market-preference is the acknowledgment that generated revenues are automatically distributed to companies in the market, rather than collected by the Government (Metz and al 2001), although it should depend on the final use of tax revenues, and markets transaction costs. In addition, the argument that the knowledge of abatement costs is not complete reinforces the uncertainty in the amounts of emissions reductions that the tax will achieve (Smith 2008), referred above as the "quantity certainty" of results.

On operational issues, emissions trading requires, in the first place, the definition of an overall limit on emissions, and the issuance of the equivalent number of permits. Market participants will need to hold the number of permits that correspond to their actual emissions. The trading of permits is allowed, thus allocating reductions to actions with lower marginal costs, regardless of the initial allocation. In this sense, by achieving optimal abatement level at a minimum cost, the cost-effectiveness of the system is ensured (Tietenberg 2003).

First microeconomic computer simulations of a cap-and-trade system for cities emissions were designed by Burton and Sanjour, between 1967 and 1970 (Burton and Sanjour 1970, Burton *et al.* 1973), for the National Air Pollution Control Administration (now called the US Environmental Protection Agency's Office of Air and Radiation - EPA). The simulation produced several insights

on emission markets operation (Burton and Sanjour 1970, Burton *et al.* 1973). In 1985 Tietenberg published a review of an emissions exchange system between plants in a same company, which EPA allowed. He shows that the system provided the right incentives for innovation and investment in emission control, presenting proof of principle that previously simulated emissions trading is a new policy instrument (Tietenberg 1985). At that time countries were having a large problem with “acid rain”, mainly caused by sulphur dioxide and nitrogen oxides, from fossil fuel-burning power plants, especially coal power plants. To deal with this issue, the first “cap-and-trade” system was conceived by C. Boyden Gray, under the Clean Air Act, as part of the US Acid Rain Program (Voß 2007, Calel 2011). Trading of permits between power plants started in 1995. Assessment studies show that the original limit or ‘cap’ goal was reached in 2007, way before the 2010 deadline, and with only one fourth of the initially expected costs (EPA 2007, Napolitano *et al.* 2007).

Other emissions cap-and-trade examples existed, although small when comparing to the Acid Rain Program in terms of participants involved and emissions’ reductions (Ellerman and Harrison Jr 2003): the “RECLAIM” program, capping NO_x (mono-nitrogen oxides) and SO₂ (sulfur dioxide) stationary emissions in the Los Angeles Basin, since 1994, and the “Northeast NO_x Budget Trading”, trading NO_x, in the Northeastern US since 1999.

On GHG, the European Union Emission Trading Scheme (EU ETS) was the first market to be implemented, in 2005. It is still by far the largest (EC 2013b), including most energy intensive sectors of the economy, currently with obligations up to 2020. In the USA, the Regional Greenhouse Gas Initiative (RGGI) started in 2009, and is a trading system for power generators. Also in the USA, the state of California has a cap-and-trade program for GHG emissions that started operations in early 2012, with mandatory compliance since January 1, 2013. Far from there, in China, four towns and a province are under regional emission markets covering power generators. Guangdong, the province, is expected to have the second-largest carbon market in the world, after the EU ETS, pairwise to the California program. Other markets for GHG exist, in Australia, New Zealand, the City of Tokyo, Kazakhstan, Switzerland, and Quebec. Most of these markets started in 2012-2013. Another three emission trading schemes are scheduled for launching, and 15 are considered for implementation, as we may see in Figure 1.

In summary, in the last 20 years we find good results from the initial studies and simulations, we have an “Acid Rain” emissions market that rendered high positive outcomes, and international policy preference for cap-and-trade rather than direct regulation or taxes. Also, the EU ETS is in its third phase, and other 12 markets are in place. We may say, against this background, that carbon markets have become officially implemented in international context. All these markets

must be liquid, transparent and efficient, to assure their primary goal of capping GHG emissions at the least cost for society.



Figure 1 : Emission trading schemes around the World

(data source: icapcarbonaction.com)

Under a cap-and-trade system, emission prices are of the utmost importance. They reflect the ‘price of pollution’, or the marginal cost of abatement, providing actors with ongoing incentives for technological changes that reduces emissions. Carbon prices present the equilibrium between demand and supply of emission permits, and consequently are the mirror of abatement decisions. Tietenberg (2010), p.3, recalls that in this scheme, prices are instantly determined, avoiding a “long iterative procedure [...] through trial and error [...] found in tax and standards system”. The carbon price also conveys useful information to climate policy, which can thus consciously decide on the overall emissions goal (Aatola *et al.* 2013b). So, expectedly, a large part of studies on carbon markets look at price variations, determinations and effects, as will be referred in the following chapters.

Looking in particular to the EU ETS, the reference carbon market because of its age and size, one can observe a very evident price decline since the beginning of its operations, in 2005. Since 2008, prices dropped from a maximum of € 28.73 to 2.7€/tCO₂e, averaging 4.4€/tCO₂e in 2013 (Bluenext and SendeCO₂ data). Also, studies have demonstrated the existence of arbitrage opportunities between spot and futures contracts (Charles *et al.* 2013). In fact, Tindale (2013) notes

that the exchange of allowances at less than 8 € / tonne is too low to encourage investment in energy efficiency or 'low carbon' energy, adding that the system has to be improved to raise prices and achieve increased stability. Finally, Löfgren *et al.* (2013) and Lundgren *et al.* (2013) show the lack of a significant effect on companies decisions to invest in the development of mitigation technologies based on low EU ETS carbon prices.

Nevertheless, the EU ETS continues to be the European Union primary climate change policy tool, presenting small, but real net emissions reductions additional to other EU sustainability measures (Branger *et al.* 2013). And so, regardless of price forecasts and criticisms, it is expected that the review of the European carbon market, which began in 2013, will establish stronger links between commitments to reduce emissions of individual European countries (Egenhofer and Alessi 2013), and will achieve some control over the price of carbon (Branger *et al.* 2013).

More recently, the European Commission presented the “2030 climate and energy goals for a competitive, secure and low-carbon EU economy” (EC 2014)². The EC proposal has six key energy-climate elements, including the reduction in GHG emissions by 40% below the 1990 level and the reform of the EU ETS. Regarding changes in the EU ETS, the EC (2014), p.1 “proposes to establish a market stability reserve [...] that would both address the surplus of emission allowances that has built up in recent years and improve the system's resilience to major shocks by automatically adjusting the supply of allowances to be auctioned”. Also, estimates by the leading source of information on carbon trading indicate prices between 21€/tCO₂e and 96€/tCO₂e for 2030 depending on the rate of economic growth (Schjølset, PointCarbon), which translates the high uncertainty about the dynamics of the carbon price and its feedback effects on other energy variables. In view of the importance that energy prices have on energy and climate issues, and, in consequence, on the EU ETS, the EC attaches to the 2014 proposal a “Report on energy prices and cost”.

Of course, GHG emissions and energy use are tangibly related, so, this relation should reveal itself in the corresponding exchange markets. Emission market fundamentals previously presented tell us that the carbon price should reflect the negative pollution externality. Thus, energy markets should act accordingly in the presence of a pollution production cost, penalizing the use of more emitting fuels. Also, changes in more or less polluting energy prices should also be reflected in the carbon price. Many authors have discussed causality between carbon and electricity, natural gas and coal prices, and, longer term effects of institutional and policy

² Presented to the European Parliament on 22/01/2014.

decisions (Asafu-Adjaye 2000, Springer and Varilek 2004, Mansanet-Bataller *et al.* 2007, Milunovich 2007, Alberola *et al.* 2008, Benz and Truck 2009, Fezzi and Bunn 2009, Mansanet-Bataller and Soriano 2009, Hintermann 2010, Keppler and Mansanet-Bataller 2010, Chevallier 2011d, Feng *et al.* 2011, Conrad *et al.* 2012, Gorenflo 2012, Sijm *et al.* 2012, Aatola *et al.* 2013a, b, Byun and Cho 2013, García-Martos *et al.* 2013, Kopp and Mignone 2013, Liu and Chen 2013, Lutz *et al.* 2013).

The studies on relations between energy and carbon prices, as typical finance markets research, follow econometric methodologies. These approaches allow to quantify relations and, more than that, test hypotheses with scientific rigor³. Within the vast econometrics models that exist, Granger causality tests (Granger 1969) have been used for interconnection analysis between CO₂ prices and other variables (Keppler and Mansanet-Bataller 2010, Creti *et al.* 2012). Although it can be repeated on both ways, Granger tests only consider a one-way influence of variables in CO₂ at each moment, while everything else remains constant. In short, the Granger causality test studies the hypothesis of one time series being statistically significant in predicting another. We may say that the series 'A' Granger-causes 'B'. However, this approach has limitations mostly because the test is designed to handle pairs of variables, problems arising when there is a possibility of the existence of a 'C' series that can move both A and B. And, in fact, the reality in carbon-energy analysis is that a feedback effect of price variations is expected (Keppler and Mansanet-Bataller 2010).

The mathematical solution to overcome the pairwise endogeneity issue is to use a vector of several endogenous variables as dependent and their lagged values as independent variables. In econometrics this is called a vector autoregression model (VAR) which is usually applied to analyse and display interdependencies between different interrelated time series. The main feature of this model is to allow the study of impulse-response functions (IRF) that consider the influence of all time series at the same time. In this function, an impulse, or innovation, is given to one variable, and responses are analysed in other variables.

There are recent studies related to carbon markets that use VAR models, but they apply this methodology to stock prices of clean energy firms, oil and carbon markets (Kumar *et al.* 2012),

³ "Reasoning on economic facts means, and always meant, within a very important sector, quantitative reasoning. And there is no logical breach between quantitative reasoning of an elementary character, and quantitative reasoning of the kind involving the use of 'higher mathematics'." Schumpeter, J. (1933). *The Common Sense of Econometrics*. *Econometrica* 1(1): 5-12., p.1.

to the role of macroeconomic indicators (Chevallier 2011c, Chevallier 2011d) or look at the impacts of changes in electricity prices (Aatola *et al.* 2013b). However, these studies are not directly related to carbon versus energy prices. There is also a study by Fezzi and Bunn (2009) that studies impulse-responses although exclusively between gas, carbon and electricity, in the UK for the first phase of the EU ETS. Finally, Gorenflo (2012) also relies on a VAR model to study the lead-lag relationship between spot and futures prices of CO₂ emission allowances. Other authors look into volatility issues, mostly through GARCH models (Benz and Truck 2009, Chevallier 2011b, Arouri *et al.* 2012, Conrad *et al.* 2012, Rittler 2012, Byun and Cho 2013, Liu and Chen 2013, Koch 2014, Reboredo 2014). A more detailed literature analysis on carbon prices is presented in the introduction of the analysis chapter, section 3.1.

In this study, we propose to go deeply on the analysis of carbon price dynamics. Looking at recent data from two large carbon trading schemes, we aim to analyse the interrelationship of CO₂ prices with the most relevant energy, economy and substitute goods influencing those markets.

Scientific contributions, research questions and proposed hypotheses

Therefore, as the first scientific contribution of this work, we specify a dynamic vector autoregression (VAR) model to estimate response functions of CO₂ prices to impulses in other variables, and vice versa. These impulse-response functions (IRF) allow us to observe the impact of CO₂ in other variables, in terms of duration, direction and magnitude.

In complement to the previous model from which we obtain short-term responses, **we also study longer cycles through wavelet analysis. This is the second scientific contribution of this work.** This analysis is done simultaneously in the time and frequency domains, in complement to the time-domain method that is a VAR. This allow us to see how carbon and energy prices behave at different frequencies and how this behaviour changes over time. Since wavelet analysis provides convenient tools to distinguish relations at particular frequencies and particular time horizons, our empirical approach has the potential to identify relations getting stronger and then disappearing over specific time intervals and frequencies. With this method, we will be able to examine the coherence of carbon and energy price variations, and lead-lag causality

relations, at different frequencies for the time period in focus. This is useful longer term information that the VAR impulse-response function does not provide. To our knowledge we are the first to apply multivariate wavelet analysis, proposed by Aguiar-Conraria and Soares (2014).

We propose to develop such a study on two carbon markets: the largest and oldest carbon market – the European, and the newest and promising Californian carbon market.

These two approaches will increase the evidence on this subject by providing us with suggestions on how much cost variation from emissions should be expected and for how long. It will deliver a causality analysis of endogenous variables expected to influence and to be influenced by the carbon price, and impact duration and direction of changes in those variables.

Our two main research questions include the identification of carbon price drivers, and effects:

What drives carbon price variations? What variations do carbon prices drive?

Following referred previous studies and carbon market fundamentals we hypothesize a possible influence of the economy, of both final and primary energies, and of carbon permits substitutes (offset credits) in the carbon price. In the reverse view, we consider that carbon prices mainly influence final energy prices, although not discarding the possibility of also influencing gas or coal prices. We propose that the influence of energy prices in CO₂ prices happens in the very short-term. We also propose that the potential impact of carbon prices in final energy prices occurs in a one year cycle, or more, if considering primary energies prices. Our methods do not impose theoretical assumptions⁴.

If we look at different variables, and consider the sectors included in the emission markets, the above presented hypotheses can be divided into several research sub-questions.

⁴ With the exception, as we will see, of the Choleski decomposition (section 2.1.2.2).

On carbon price drivers:

1. Do final energy prices impact carbon price?

We hypothesize positive immediate reactions from impacts of electricity and gasoline.

2. Do primary energy prices impact carbon price?

We expect so, in a very immediate term, and expect a positive relation originating from gas prices, and negative from oil and coal. Regarding the existence of substitutes for carbon licences, we do not expect a significant effect on the carbon price.

3. Finally, on the macroeconomic perspective, does the level of economic activity translates into the carbon market?

Yes, we hypothesize a positive, fast, reaction.

On carbon price effects:

1. Does carbon price influences final energy prices, including electricity and gasoline?

We hypothesize a positive relation.

2. Does carbon prices influence primary energy prices, including natural gas, coal and oil?

We hypothesize a negative relation towards coal prices and positive relation regarding gas and oil.

3. Does the permit price impact the offset price (CER) in the EU ETS?

In the EU ETS, CERs, or credits from emission reduction projects (offsets) may be used in a limited way as alternative compliance tool to the European Union allowance. We expect so and with immediate response.

In the context of the economic crisis affecting Europe since 2007, and for the proper start-up of the Californian market, it is particularly important to respond to the previous questions, identifying what drives carbon prices and how they do reflect market fundamentals. A detailed study of this matter carries valuable results to policy and production decisions. Only with a more comprehensive knowledge on carbon price origins and effects, a proper evaluation of the market policy effectiveness will be possible and market actors will be able to implement necessary measures to obtain the desired outcomes of reducing emissions, moving towards efficiency.

This document follows a very simple structure: in chapter two we describe the econometric theory used in the VAR models and Wavelet analysis. The wavelet section has more detail because we use instruments not yet used (*e.g.* multivariate wavelet analysis). Chapter three characterizes the European and the Californian markets, data, and results. In chapter four we discuss the methodology and comment on policy implications from both models and markets, and finally chapter five concludes and proposes directions for further research.

2 METHODOLOGY

In this chapter we present the methodological and theoretical framework, essentially from a mathematical standpoint.

First we present the construction of the vector auto-regressive model and finally the deduction of the partial multivariate analysis tools is outlined.

The application of this method to our analysis is justified in the introduction to Chapter 3. At that point, after this theoretical background, the interest of this innovative approach to the analysis of carbon prices will become clear.

The data and MatLab scripts necessary to replicate all our wavelet analysis results are available for download at <http://sites.google.com/site/aguiarconraria/joanasoares-wavelets>. In the same website, the reader can find and freely download a wavelet MatLab toolbox, The ASToolbox, written by Maria Joana Soares and Luís Aguiar-Conraria. Regarding the VAR analysis, the Eviews data files necessary to replicate all our results are available for download at <http://www.rita-sousa.com>.

2.1 The Vector Autoregression Model (VAR)

2.1.1 Background on VAR models

In time series, a vector autoregression (VAR) model is a natural expansion of the one-variable autoregression model (AR). In an AR model the variable depends on its past values, whereas a VAR model allows for a vector of several evolving variables. VAR models became famous in Christopher A. Sims' paper "Macroeconomics and Reality" (Sims 1980). They are linear models with n variables, thus n equations, where each variable is explained by its own lagged values and present and past values of all other variables. In this section we contextualize the use of VAR models and in the next present the VAR theory.

There is a substantial number of relevant references on VAR time series models (Tiao and Tsay 1989, Amisano and Giannini 1997, Stock and Watson 2001, Enders 2008, Tsay 2010, Peña *et al.* 2011). The following demonstrations are necessarily brief, because the methodology is of standardized use.

The VAR framework delivers an efficient and flexible way to observe the dynamics in multiple time series. As Stock and Watson (2001) p.1 pose, the VAR work by Sims, *“held out the promise of providing a coherent and credible approach to data description, forecasting, structural inference, and policy analysis”*. It has been widely used to analyse economic and financial time series and for forecasting. However, the problem of defining causality with several variables is still challenging, and institutional knowledge and economic theory must always be considered in the analysis of the model results. This is especially important in structural inference and policy analysis, because it is necessary to impose assumptions regarding the causal structure.

A central outcome of VAR models is that it allows to estimate the dynamic response of a variable to innovations in other variables through a set of impulse-response functions (IRF), after appropriate restrictions identification.

Causality issues are usually analysed following a Granger-causality test (Granger 1969). A variable x is said to Granger-cause a variable y if, given the past values of y , past values of x are useful in forecasting y . VAR models can also be used for testing Granger-causality. Granger causality relies on correlation between the current value of one variable and the past values of other, so, if we test for joint the significance of the lagged independent variables, we are testing for Granger causality. However, it is possible that we find Granger causality in both directions, allowing for feedback mechanisms. It is also possible that both variables are driven by a third variable. In this situation it would not be advisable to use a Granger test, because it is designed to analyse relation between two variables. It may produce distorted results when considering three or more variables (Stern 2011). In alternative, the Wald test, or block exogeneity test, checks for variables exogeneity, considering more than two variables, thus, may be applied to VAR models with n variables. The null hypothesis in the Wald test is that a set of parameters coefficients is equal to a specific value, in our case, zero. If we do not reject H_0 , then it suggests that the variables are possibly exogenous.

In short, the Wald test checks for Granger causality in a VAR model: for each equation and each endogenous variable that is not the dependent variable in that equation, we compute Wald tests that the coefficients on all the lags of an endogenous variable are jointly zero, and, that each of the other endogenous variables does not Granger-cause the dependent variable in that equation.

Specification issues: variables and lags

To correctly specify a VAR model we need not only to decide on which variables to include, but also on the number of lags. On this regard, it is possible to rely on information criteria, or formal testing. The Akaike (AIC) and Schwarz-Bayesian (SIC) information criteria are the most common methods used. However, information criteria are not tests, so they mainly indicate the goodness of fit of alternative lag number. The alternative is to use formal testing with the Likelihood Ratio (LR)⁵, which we used in the models presented in sections 3.2.3 and 3.3.3 (VAR analysis of EU and CA, respectively).

In what follows we present two VARs representations, which will be one of the workhorses of our empirical analyses: the structural (SVAR) and the reduced form (VAR). In the SVAR we follow econometric theory by Sims (1980) to define the causality relation between variables in the contemporaneous period. The main feature is that Sims uses the Cholesky decomposition of the VAR variance-covariance error matrix. Others decomposition methods exist, such as Blanchard and Quah (1989), this one more adequate to long-run restrictions. The reduced form VAR, deduced from the SVAR, considers a serially uncorrelated error term, where each equation is estimated by ordinary least squares, and allows the estimation of the impulse-response functions.

2.1.2 Theory of a VAR model

2.1.2.1 VAR Analysis

As previously introduced, a vector auto-regressive model presents the simultaneous evolution of a set of variables. These variables are endogenous, which is saying that they evolve as a function of all their previous values. They may be represented in a vector Y_t , where t is the period observed in each of the n variables:

$$Y_t = [y_{1t} \quad y_{2t} \quad \dots \quad y_{nt}]^T \quad (1)$$

⁵ The LR test statistic is: $LR = (T - m)(\ln|\Sigma_r| - \ln|\Sigma_u|) \sim \chi^2(q)$ with T = number of observations (after lags); m = number of estimated parameters in equations of the unrestricted system; $|\Sigma_{r/u}|$ = determinant of the covariance matrix of residuals of the restricted (r) and unrestricted (u) system; q = total number of restrictions = number of lags \times number of variables².

In this work our time series will include carbon prices, electricity prices, and natural gas prices, among others, as presented next in section 2.2.1.

For simplicity purposes, following Enders (2008), we first show the determination of a two variables and one lag, or, VAR(1) model. Then, we generalize to a VAR(p) of n variables.

Consider the following model with two variables that depend simultaneously on each other and also on their lagged value:

$$\begin{aligned} y_{1t} &= c_{10} - b_{12} \cdot y_{2t} + c_{11} \cdot y_{1,t-1} + c_{12} \cdot y_{2,t-1} + \varepsilon_{y_1 t} \\ y_{2t} &= c_{20} - b_{21} \cdot y_{1t} + c_{21} \cdot y_{1,t-1} + c_{22} \cdot y_{2,t-1} + \varepsilon_{y_2 t} \end{aligned}$$

Where $\varepsilon_{y_{it}}$ is an i.i.d. error term with mean zero, with $cov(\varepsilon_{y_1}, \varepsilon_{y_2}) = 0$. In matrix form:

$$\begin{bmatrix} 1 & b_{12} \\ b_{21} & 1 \end{bmatrix} \begin{bmatrix} y_{1t} \\ y_{2t} \end{bmatrix} = \begin{bmatrix} c_{10} \\ c_{20} \end{bmatrix} + \begin{bmatrix} c_{11} & c_{12} \\ c_{21} & c_{22} \end{bmatrix} \begin{bmatrix} y_{1,t-1} \\ y_{2,t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{y_1 t} \\ \varepsilon_{y_2 t} \end{bmatrix}$$

Which can be written more compactly written as:

$$BY_t = \Gamma_0 + \Gamma_1 Y_{t-1} + \varepsilon_t \quad (2)$$

Equation (2) is called the **structural VAR (SVAR)**.

Matrix B reports the contemporaneous relations between variables, or, in other words, the effect that a variable in one moment has in the other in that same moment. So the model allows for feedback effect because variables at time 't' may affect each other.

Unfortunately, equation (2) cannot be estimated directly by ordinary least squares (OLS), as they would render inconsistent estimates.

To avoid this problem, one can pre-multiply all equation by B^{-1} :

$$B^{-1}BY_t = B^{-1}\Gamma_0 + B^{-1}\Gamma_1Y_{t-1} + B^{-1}\varepsilon_t$$

Which may be simplified to an unstructured VAR usually called **VAR**, in standard form:

$$Y_t = A_0 + A_1Y_{t-1} + e_t \quad (3)$$

The new error terms e_t are composites of the ε_t errors, or innovations, from the SVAR.

Equation (3) delivers the VAR in its reduced form and can be estimated by OLS. Note that the e_t 's have zero mean and constant in time independent variances, but their covariances are not zero, meaning that although they are serially uncorrelated, they are correlated across equations. I.e., the shocks in the model are correlated.

For clarity, we may represent the result of the 2 variables VAR(1) in the matrix form:

$$\begin{bmatrix} y_{1t} \\ y_{2t} \end{bmatrix} = \begin{bmatrix} a_{10} \\ a_{20} \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} y_{1,t-1} \\ y_{2,t-1} \end{bmatrix} + \begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix} \quad (4)$$

Generalizing the model to n variables and p lags, a vector auto-regressive model explains the value of all variables included in vector Y_t in current period t with their own values in previous periods. It is an auto-regression of the vector of variables in previously determined p lags, also called a p th-order VAR. Following equation (2), the SVAR(p) may be written as:

$$BY_t = \Gamma_0 + \Gamma_1Y_{t-1} + \Gamma_2Y_{t-2} + \cdots + \Gamma_pY_{t-p} + \varepsilon_t, \quad \forall (t, p) \in \mathbb{N} \quad (5)$$

And then, again, pre-multiplying by B^{-1} , we obtain the VAR model:

$$Y_t = A_0 + A_1Y_{t-1} + A_2Y_{t-2} + \cdots + A_pY_{t-p} + e_t, \quad \forall (t, p) \in \mathbb{N} \quad (6)$$

In equation (6), $A_1 \dots A_p$ represent the matrices of the variables values in each lag.

Next, we represent the model in lag polynomials to make it more practical⁶. We may then represent equation (5), the SVAR(p), as:

$$BY_t = \Gamma_0 + \Gamma_1(L)Y_{t-1} + \varepsilon_t \quad (7)$$

And finally obtain the VAR(p):

$$Y_t = A_0 + A_1(L)Y_{t-1} + e_t \quad (8)$$

Again, equation (8) delivers the VAR in its reduced form and can be estimated by OLS. Once more, as in equation (3), e_t 's have zero mean and constant time independent variances, but their covariances are not zero, meaning that although they are serially uncorrelated, they are correlated across equations. I.e., the shocks in the model are correlated.

This can easily be illustrated in a VAR(1), 2 variables, example. Recalling the matrix B as representative of the contemporaneous effects, and from equation (3) that:

$$e_t = B^{-1}\varepsilon_t \quad (9)$$

From linear algebra analytical inverse matrix determination, we have:

$$B^{-1} = \frac{1}{|B|}(B^*)^T = \frac{1}{1 - b_{21}b_{12}} \begin{bmatrix} 1 & -b_{12} \\ -b_{21} & 1 \end{bmatrix}$$

With the adjugate matrix $= (B^*)^T$, or, the transposed cofactor matrix.

Rewriting (9) in matrices:

⁶ Lag operator, or backshift operator L : $LY_t = Y_{t-1}$ or $LY_{t+1} = Y_t$, then $L^{-1}LY_t = L^{-1}Y_{t-1} \Leftrightarrow Y_t = L^{-1}Y_{t-1}$, which can be generalized to $Y_t = L^{-k}Y_{t-k}$.

$$\begin{bmatrix} e_{2t} \\ e_{1t} \end{bmatrix} = \frac{1}{1 - b_{21}b_{12}} \begin{bmatrix} 1 & -b_{12} \\ -b_{21} & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_{y_1t} \\ \varepsilon_{y_2t} \end{bmatrix}$$

With the solutions:

$$e_{1t} = \frac{\varepsilon_{y_1t} - b_{12}\varepsilon_{y_2t}}{1 - b_{21}b_{12}} \quad \text{and} \quad e_{2t} = \frac{\varepsilon_{y_2t} - b_{21}\varepsilon_{y_1t}}{1 - b_{21}b_{12}}$$

Because ε_{y_1t} and ε_{y_2t} are white noise, a stationary time series or a stationary random process with zero autocorrelation, then e_{1t} and e_{2t} have the following moments:

$$E(e_{it}) = 0$$

$$Var(e_{1t}) = E(e_{1t}^2) = \frac{E(\varepsilon_{y_1t}^2 + b_{12}^2\varepsilon_{y_2t}^2)}{(1 - b_{21}b_{12})^2} = \frac{\sigma_{y_1}^2 + b_{12}^2\sigma_{y_2}^2}{(1 - b_{21}b_{12})^2} \quad (10)$$

We obtain similar results to equation (10) for $Var(e_{2t})$.

On covariance:

$$\begin{aligned} Covar(e_{1t}, e_{2t}) &= E(e_{1t} \cdot e_{2t}) = \\ &= \frac{E[(\varepsilon_{y_1t} - b_{12}\varepsilon_{y_2t})(\varepsilon_{y_2t} - b_{21}\varepsilon_{y_1t})]}{(1 - b_{21}b_{12})^2} = \frac{-b_{21}\sigma_{y_1}^2 - b_{12}\sigma_{y_2}^2}{(1 - b_{21}b_{12})^2} \neq 0 \end{aligned} \quad (11)$$

So, the shocks in the SVAR are correlated. The contemporaneous effects reflected in matrix B by b_{12} and b_{21} would have to be zero in order to obtain a 0 covariance.

2.1.2.2 Cholesky decomposition

Given the contemporaneous effects presented in B , it is not possible to use OLS to estimate the SVAR. To overcome this issue, one has to estimate the VAR in the reduced form. Unfortunately, from that estimation it is not possible to recover the structural parameters of interest. To do so, one needs to add extra restrictions.

We follow the methodology proposed by Sims (1980) and rely on the Cholesky decomposition to impose short run identification restrictions. The idea is to impose restrictions in the error covariance matrix of equation (8) in order to recover matrix B of equation (7). These restrictions impose contemporaneous effects of zero in a predetermined direction. By a convenient ordering the variables, we basically impose that the covariance matrix is lower triangular where the first equation does not consider any other innovation rather than its own, the second equation considers the second and the first coming from the addition of the first equation and so on, until the last equation that considers them all. In the VAR(1) example, with a Cholesky decomposition⁷, B matrix becomes:

$$B = \begin{bmatrix} 1 & 0 \\ b_{21} & 1 \end{bmatrix} \text{ thus } B^{-1} = \begin{bmatrix} 1 & 0 \\ -b_{21} & 1 \end{bmatrix}$$

hence VAR(1):

$$\begin{aligned} \begin{bmatrix} y_{1t} \\ y_{2t} \end{bmatrix} &= \\ &= \begin{bmatrix} c_{10} \\ c_{20} - b_{21}c_{10} \end{bmatrix} + \begin{bmatrix} c_{11} & c_{12} \\ c_{21} - b_{21}c_{11} & c_{22} - b_{21}c_{12} \end{bmatrix} \begin{bmatrix} y_{1,t-1} \\ y_{2,t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{y_1t} \\ \varepsilon_{y_2t} - b_{12}\varepsilon_{y_1t} \end{bmatrix} \end{aligned} \quad (12)$$

Comparing equations (4) and (12) we obtain the coefficients of the VAR:

⁷ Considering a symmetric positive-definite matrix A , a Cholesky decomposition factorizes A into the product of a lower matrix (L) times its conjugate transpose (L^*): $A=LL^*$. All symmetric positive-definite matrices have a single Cholesky decomposition.

$$\begin{aligned} a_{10} &= c_{10}, & a_{11} &= c_{11}, & a_{12} &= c_{12}, & e_{1t} &= \varepsilon_{y_1t} \\ a_{20} &= c_{20} - b_{21}c_{10}, & a_{21} &= c_{21} - b_{21}c_{11}, & a_{22} &= c_{22} - b_{21}c_{12}, & e_{2t} &= \varepsilon_{y_2t} - b_{12}\varepsilon_{y_1t} \end{aligned}$$

It is visible in the previous deduction that results will depend on the chosen variable order of impact in the contemporaneous period. In the example, if instead we had considered $b_{21}=0$, the results would have been different. Changing the order does not render significative changes in the results when the correlation between errors is small (Enders 2008).

2.1.2.3 Impact multipliers and Impulse Response Functions (IRF)

An impulse, or an impelling force or motion, is what is assumed to trigger the dynamic response of the model. The goal is the analysis of the response, the propagation mechanism, of the variables in the following time periods. The IRF shows the effect of a particular innovation to variable i ($\varepsilon_{i,t}$) on the contemporaneous and future values of all variables.

The process to define these functions starts with the estimated 'composite' e_t residuals (linear combinations of uncorrelated innovations) and from them rebuilds the original innovations ε_t . The process involves representing the VAR model as a Vector Moving Average (VMA) where endogenous variables are defined by e_t shocks (Sims 1980). The VMA allows tracking the shocks effects. To see this, note that equation (8) may be rewritten as:

$$A(L)Y_t = e_t \tag{13}$$

Where, for simplicity, we dropped the constants and $A(L) = (I - A_1(L))$.

Then, considering the VAR model is invertible, it is possible to write equation (13) as a Vector Moving Average of infinite order $VMA(\infty)$:

$$Y_t = A^{-1}(L)e_t = A^{-1}(L)B^{-1}\varepsilon_t = \Phi(L)\varepsilon_t \tag{14}$$

It should be clear from equation (14), that with a VMA representation, and keeping in mind that $e_t = B^{-1}\varepsilon_t$, it is possible to estimate the impulse response function. Given a unit change in innovation 'j', or impulse, the system reaction to a shock is given by individual reactions of variables 'i', which may be called impact multipliers:

$$\frac{\partial y_{i,t+s}}{\partial \varepsilon_{j,t}} = \Phi_{i,j}(s) \quad (15)$$

Equation (15) shows the impact effect of a one unit change in ε_j , a structural innovation, on y_i , in s lags. Impulse response functions (IRF) are the representation of the effects of structural innovations on current and future values of considered variables $\Phi_{i,j}(0), \Phi_{i,j}(1), \Phi_{i,j}(2), \dots$. They are the time path of dependent variables. For each n variables model we have n^2 IRFs.

When the system of equations is stationary, the impact also becomes stable after some periods. However, if it is not, we may see an explosive time path in the IRF.

2.2 Multivariate Wavelets Analysis

2.2.1 Background on wavelet analysis

In the previous section, we considered the simultaneous analysis of multiple variables dynamically explained by all of them in past periods. This is a very useful approach if we consider a fixed frequency of data, in this case, daily prices. However, in a time series there may exist periodic signals which vary in amplitude and frequency over time, and therefore provide additional information beyond that observed at a fixed frequency. This additional information may or may not be captured depending on the methodology used, but one cannot deny the possibility of existence of different cycles in the same time series.

Torrence and Compo (1998) present a very evident example of overlapping temporal information at different frequencies: the analysis of sea surface temperature in the equatorial Pacific Ocean. The most visible temperature variability, originating from the "El Niño - Southern Oscillation" (ENSO), has irregular cycles of 2 to 7 years. But this variation overlaps other longer fluctuations of decades, which modulate the amplitude and occurrence of the phenomena of El Niño, as shown in Figure 2:

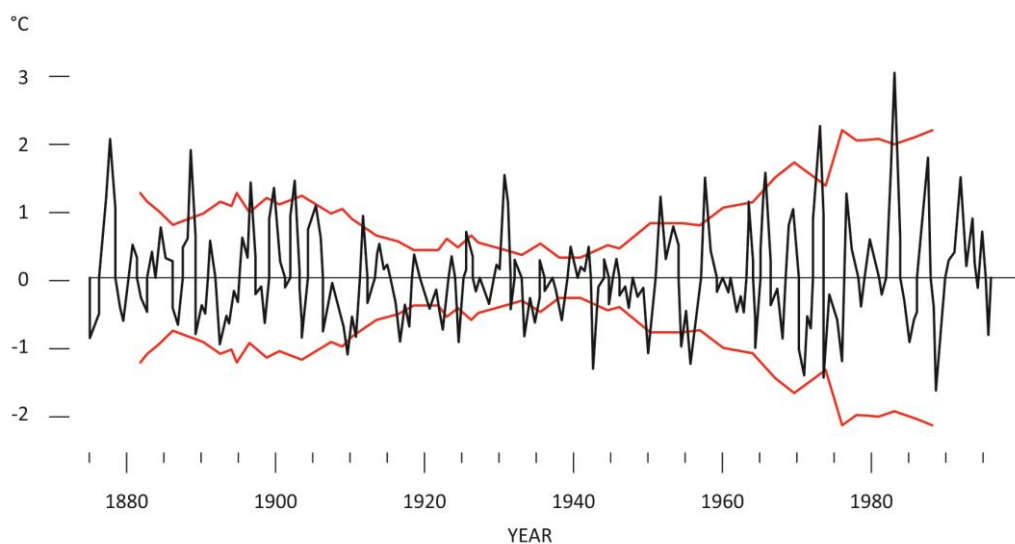


Figure 2 : Sea surface temperatures averaged over the NINO3 area in the eastern Pacific.

Data source: (Torrence and Compo 1998). Black represents the averaged sea surface temperatures of the area 5°S-5°N, 90°W-150°W. Red shows the running 15-year variance, plotted at mid-point, and mirrored to show "envelope" of variance.

As the authors show, the simplest method of analysing a non-stationary time series would be to analyse differences in statistics such as mean and variance in different periods of time. Accordingly, in Figure 2 the authors also present the evolution of a 15 years variance (red line). One can see that ENSO had more variation during 1880-1920 and since 1950, also with a relatively quiet period during 1920-1950. For analysis of different effects, it would be convenient to separate fluctuations over short vs longer periods.

However, this approach has two problems. Firstly the choice of the time length for the variance calculation sets *a priori* the shape of the red curve, which is a localization problem in time. The longer the time interval considered for variance calculation, the smoother the curve would be. In other words, the lower the frequencies, the smoother is the curve, and periodic signals are lost. While the reverse, high frequencies, present too many oscillations, and the temporal information is lost. Secondly, the successively calculated variance does not hold information about the frequency (Torrence and Compo 1998).

To solve these issues, first it would be necessary to consider a adjustable time-length for calculating the variance, to solve the problem of localization in time. For the question of the localization in frequency, one could use the Fourier transform of time in frequency, sliding it over time, and calculating it on each cycle.

Fourier analysis supports the issue of localization in frequency. Born in the early nineteenth century, it is the study of how functions can be approximated by sums of simpler trigonometric functions. The Fourier transform is, thus, a mathematical transformation that converts signals between the time domain and the frequency domain (Figure 3). The amplitudes of the signals originate a frequency spectrum of the original function in the temporal domain.

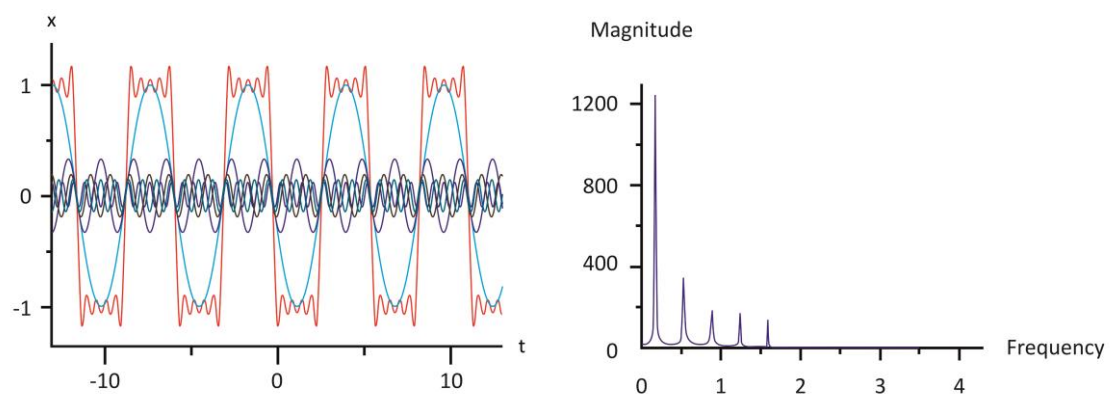


Figure 3 : The Fourier transform of a time series

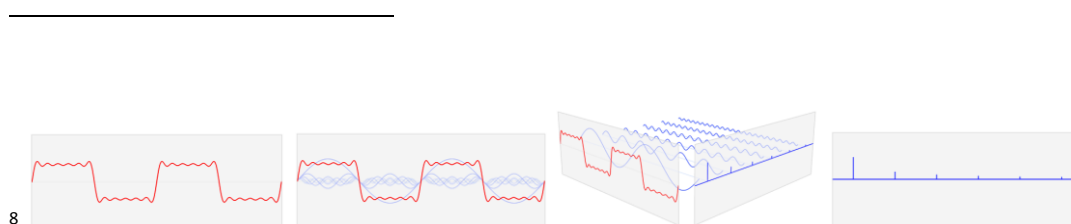
The red curve is a periodical function which can be approximated by a sum of simple sine functions. At the right we have the Fourier transform of the original function⁸.

The main problem with the Fourier transform is that when analysing the information in the frequency domain one loses the temporal information (Bloomfield 2004).

This approach allows to obtain information known as the “power spectrum” of a time series. It is also called spectral analysis. It describes how the variance of the data is distributed over the frequencies at which the time series can be decomposed. That is, the variance distribution as a function of the frequency range. The power spectrum is related to the auto-covariance (ACV), a concept more easily recognized to social scientists⁹. In fact, the power spectrum contains the information displayed in the ACV, but in a complementary perspective because the ACV is a function of time while the power spectrum is a function of frequency. The power spectrum may present new information because data variability may be frequency dependent.

Spectral analysis has also been used in economics research, such as the study of business cycles, of relations between different economic variables, military spending, the governments popularity, among others (Granger 1966, Richards 1992, Gerace 2002, Wen 2005). Yet, despite its usefulness, it has the problem of the analysis of temporal information. Moreover, the Fourier power spectrum analysis is only useful on stationary time series, not recommended for situations where cycles do not have fixed periodicity (Goldstein 1988).

Wavelet analysis attempts to solve the problem of simultaneous localization in time and frequency. It gives information on the amplitude of the cyclic signals, and how this amplitude varies with time. It is a useful tool for analysing changes in the variability of data in a time series. It



(Source: Wikimedia commons – Fourier Transform) The red curve is a periodical function which can be approximated by a sum of simple sine functions, plotted in blue in the graphs at the centre. The right-most curve is the Fourier transform of the original function.

⁹ The auto-covariance of x_t is the covariance of x over a time-shifted value. Considering $E[x_t] = \mu_t$, then the auto-covariance is $ACV_{xx}(t, s) = E[(x_t - \mu_t)(x_s - \mu_s)]$.

allows to decompose a time series in the time-frequency space and makes it possible to analyse what are the main existing cycles and how these cycles are modified over time.

The theory of wavelets was developed in the 1980s and since then it has been used in various fields, including physics, geophysics, oceanography, signal processing, harmonic analysis, and scientific computation. Studies include the study of tropical convection, the El Niño - Southern Oscillation, atmospheric cold fronts, the dispersion of ocean waves, wave growth and breaking and coherent structures in turbulent flows (Torrence and Compo 1998), among many others.

Following the previous example of Figure 2, of sea surface temperatures, below in Figure 4, we present the respective wavelet power spectrum. In following pages, we will show how wavelet transforms are obtained and how their tools, such as the power spectrum, are applied.

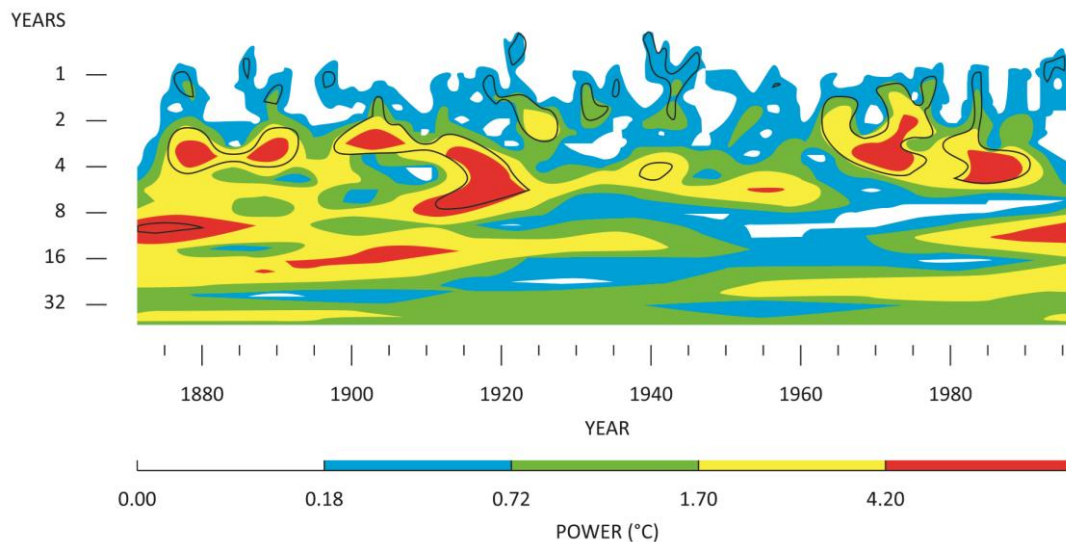


Figure 4 : Wavelet power spectrum of sea surface temperatures in the eastern Pacific

Data source: (Torrence and Compo 1998). Wavelet power spectrum of Figure 2. Black contours represent 10% significance regions. Red areas indicate high El Niño activity.

Specifically in economics, Crowley (2007) develops a guide for wavelet use and others apply these tools to various issues, including the decomposition of economic relationships of expenditure and income (Ramsey and Lampart 1998a, b), to exchange rates (Gençay *et al.* 2001a, Wong *et al.* 2003), monetary policy (Aguiar-Conraria *et al.* 2008, Rua 2012), Phillips curve (Gallegati *et al.* 2011), business cycles (Baubeau and Cazelles 2009, Aguiar-Conraria and Soares 2011a, Caraianni 2012), stock markets (Gençay *et al.* 2001b, Fernandez 2005, Gençay *et al.* 2005,

Gallegati 2008, Rua and Nunes 2009, Alvarez-Ramirez *et al.* 2012, Fernández-Macho 2012), and also commodities prices (Connor and Rossiter 2005) and energy commodities and oil prices (Aguar-Conraria and Soares 2011b, Jammazi 2012, Vacha and Barunik 2012, Reboredo and Rivera-Castro 2014).

However, all these approaches consider one, or two at most, dependent variables. Therefore, they exclude the possibility of examining other effects that may be included in the study, via third variables. With the development of multivariate analysis by Aguiar-Conraria and Soares (2014) it is now possible to analyse the relationship of one time series with many others, controlling for the effects of each of them, and then getting information on the interdependence between variables.

To our knowledge, this is the firstly known application of multivariate analysis. We consider it to be most valuable to our study because of the existence of inter-relationships and known feedback effects between energy and carbon prices.

In the following sections, we provide the theoretical framework of the wavelet multivariate analysis tools.

2.2.2 Theory of multivariate wavelets

In this section we start by reviewing the Fourier and the Gabor transforms. After, we define the continuous wavelet transform and present the three wavelet tools used:

- The wavelet power spectrum, which describes the evolution of the variance of a time-series at the different frequencies, with periods of large variance associated with periods of large power at the different scales,
- The cross-wavelet power of two time-series, which describes the local covariance between the time-series, and the wavelet coherence, which can be interpreted as a localized correlation coefficient in the time frequency space, and
- The phase, which can be viewed as the position in the cycle of the time-series as a function of frequency, and the phase-difference, which gives us information on the delay, or synchronization, between oscillations of the two time-series.

The previous tools are standard but important for the introduction of the concepts of partial and multiple wavelet analysis, given later in this section.

2.2.2.1 The Fourier and the Gabor transforms

As mentioned, Fourier analysis gives us the possibility to represent any function as an approximation of sums of sines and cosines. The Fourier transform (indicated by $\hat{\cdot}$) of the time series $x(t)$ is a function of the angular frequency ω , given by the following equation:

$$\hat{x}(\omega) = \int x(t) (\cos(\omega t) - i \sin(\omega t)) dt \quad (16)$$

Note: for simplicity reasons we consider all integrals in MWA sections to be $\int_{-\infty}^{+\infty}$.

The angular frequency ω is related to the 'ordinary' or temporal frequency f by the relationship $f = \frac{\omega}{2\pi}$. This frequency corresponds to the number of repeated occurrences of an event per unit of time. The period corresponds to the duration of this event.

As equation 16 above shows, in the Fourier transform, the information on time (t) is lost. An approach that initially aims to overcome this problem, and include t , is known as the Short Time Fourier Transform (STFT). This selects a 'window-function' g , defined in time, which allows to locate, in t , the Fourier transform. A window is a function well localized in time, *i.e.* a function with very fast decay in time, taking negligible or zero values outside a given range. Accordingly, when multiplying any function by a window, the product value will also be almost zero outside this window. The function to be transformed is thus multiplied by this 'window', only becoming visible in the part where the functions overlap.

Gabor (1946), in his transform, used a Gaussian¹⁰ as a window function, so this particular case becomes known as the Gabor transform. Gabor considers the Gaussian function as one that offers the best trade-off between resolution in time and frequency.

As this Gaussian window is shifted, their Fourier transforms are then computed. Thus, the Gabor transform G is a function of two parameters: the frequency ω , and the time shift (or translation)

¹⁰ A Gaussian function is of the form $f(x) = ae^{\left(-\frac{(x-b)^2}{2c^2}\right)} + d, \{a, b, c, d\} \in \mathbb{R}$.

parameter τ . $G(\tau, \omega)$, is defined in equation 17, as a Fourier transform of $x(t)g(t - \tau)$, a function representing the magnitude and phase of the signal in time and frequency.

$$G(\tau, \omega) = \int x(t)g(t - \tau) (\cos(\omega t) - i \sin(\omega t)) dt \quad (17)$$

A representation of the function $x(t)$ in time and frequency is thus obtained.

However, the immediate problem that arises with the Gabor transform is that it provides a fixed time-frequency resolution, since g is a fixed window with a fixed size. Morlet, along with Goupillaud and Grossmann, developed the work of Gabor, modifying it to what came to be the first formalization of the continuous wavelet transform (Goupillaud *et al.* 1984).

2.2.2.2 The continuous wavelet transform

In this transform, wavelets are used as window functions. For a function $\psi(t)$ to qualify for being a 'mother wavelet' the minimum requirements are that ψ is a square integrable function¹¹ and fulfils an admissibility condition. The *admissibility condition* is a technical condition which justifies the 'wavelet' name because it makes ψ an oscillatory function (Farge 1992).

Considering $\hat{\psi}(\omega)$ the Fourier transform of $\psi(t)$, the admissibility condition requires that:

$$\int \frac{|\hat{\psi}(\omega)|^2}{|\omega|} d\omega < +\infty \quad (18)$$

Equation 18 implies that the Fourier transform of the wavelet vanishes at the zero frequency. It is possible to show that a zero value of the Fourier transform at zero frequency also means that the wavelet's expected value in the time-domain is zero: $\int \psi(t)dt = 0$. This makes it an oscillatory function, behaving like a wave.

The 'mother wavelet' $\psi(t)$, oscillatory, represents all possible dilations by a scaling/compressing s factor and translations in time by a τ factor.

¹¹ A function for which the integral of the square of the absolute value is finite, thus satisfying $\int_{-\infty}^{\infty} |\psi(t)|^2 dt < \infty$. This integral is known as the energy of ψ , and equal to its square norm = $\|\psi(t)\|^2$.

The 'child wavelets' $\psi_{\tau,s}(t)$ are, thus, obtained by scaling and translating $\psi(t)$, which makes them functions of time and frequency localizations given by the following equation 19¹²:

$$\psi_{\tau,s}(t) = \frac{1}{\sqrt{|s|}} \psi\left(\frac{t-\tau}{s}\right), \quad s, \tau \in \mathbb{R}, s \neq 0 \quad (19)$$

So, s controls the width of the wavelet, and τ controls the localization (in time) of the wavelet.

Scaling a wavelet simply means stretching it, if $|s| > 1$, or compressing it, if $|s| < 1$, while translating it simply means shifting its place in time.

The analysis of the wavelet transform we use is known as the continuous wavelet transform (CWT). Given a time-series $x(t)$, its CWT with respect to the wavelet $\psi_{s,\tau}(t)$ is a function of two variables $W_x(\tau, s)$:

$$W_x(\tau, s) = \int x(t) \psi_{s,\tau}^*(t) dt \quad (20)$$

** means complex conjugation.*

Equation 20 shows how the time series $x(t)$ is decomposed into a set of functions $\psi_{s,\tau}(t)$, the wavelets.

The square integrable requirement mentioned previously as a property of $\psi(t)$, exists to guarantee that the integral on equation 20 converges, i.e., so that the scalar product of the wavelet function with the time series exists. Also, the admissibility condition is imposed to guarantee that the original function can be reconstructed from its CWT.

In summary, the continuous wavelet transform is used to separate a time-varying function in wavelets. Note that the wavelet function itself is not yet defined. Under wavelet properties, there are many types of wavelet functions, adaptable to different interests. Further bellow in section 2.2.2.3 we will focus on a particular one, the Morlet wavelet, useful to our work.

¹² $\frac{1}{\sqrt{|s|}}$ is the energy normalization factor, introduced to guarantee preservation of the unit energy, $\|\psi_{\tau,s}\| = 1$.

2.2.2.3 The Morlet wavelet: optimal joint time-frequency concentration

There are different types of wavelets that can be used depending on the research goals. Wavelet functions are subdivided into discrete and continuous, and the latter may be real or complex functions. Examples of discrete wavelets include the Daubechies, Haar, ..., and continuous wavelets are, for example, the Mexican hat (real) or the Morlet (complex) amongst many others.

In our study, we use the Morlet wavelet function, consisting of a modulated Gaussian, or in other words, a complex exponential function multiplied by a Gaussian window. It was first introduced in Goupillaud *et al.* (1984). The Morlet 'mother wavelet' is defined by equation 21:

$$\psi_{\omega_0}(t) = \pi^{-\frac{1}{4}} e^{i\omega_0 t} e^{-\left(\frac{t^2}{2}\right)} \quad (21)$$

We illustrate the real part of a Morlet wavelet in the following Figure 5, given by the product of a cosine function by a Gaussian.

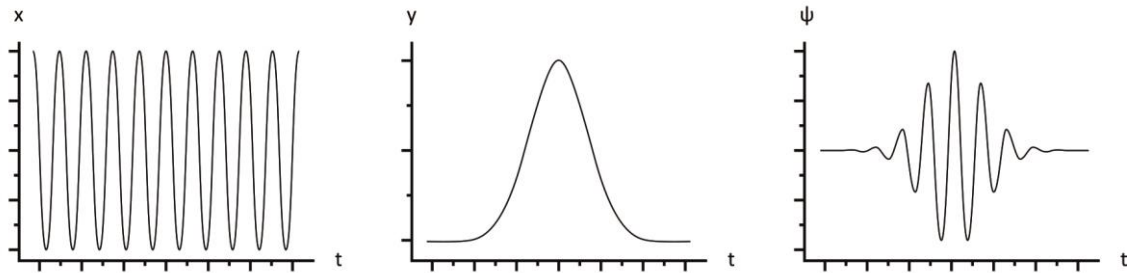


Figure 5 : The real part of a Morlet wavelet

The function on the right represents the real part of a Morlet wavelet, and results from the product of a cosine function (function on the left) by a Gaussian (function in the middle).

Strictly speaking, the Morlet wavelet is not a true wavelet because it does not fulfil the admissibility condition. However, for a large enough ω_0 (>5.5), the Morlet wavelet may be interpreted

as such, for the errors due to non-zero mean are smaller than the typical computer round-off errors (Farge 1992)¹³.

For our applications, it is essential to choose a complex wavelet, as it yields a complex transform, with information on both the amplitude and phase, crucial to study the cycles synchronism between different time-series. With real functions, there is no access to the phase information, available in the imaginary component.

It is also important to note an inverse relationship between f (which is a unit easier to visualize) and ω , *i.e* when it a function is expanded in the time domain it is also contracting in the frequencies space. This relationship is general and comes from the transform properties.

For the particular choice $\omega_0 = 6$ we have $f = \frac{\omega_0}{2\pi s} = \frac{6}{2\pi s} \approx \frac{1}{s}$. With this ω_0 , there is a very simple one-to-one relation between scale and frequency and we can use both terms interchangeably. This makes the interpretation of results more perceptible, especially in social sciences where it is more common to think of frequencies rather than on scales.

The Morlet wavelet has an important property: it has optimal joint time-frequency concentration. The Heisenberg principle says that one cannot be simultaneously precise in the time and the frequency domain. Theoretically, the time-frequency resolution of the continuous wavelet transform is bounded by the so called Heisenberg box. A "Heisenberg box" is located in the time-frequency plane: a rectangle with a time width and a frequency height. It represents a time-frequency localization. The area of the Heisenberg box describes the trade-off relationship between time and frequency and is minimized with the choice of the Morlet wavelet, since it is, in its essence, a Gaussian.

¹³ The scale refers to the width of the wavelet, so as it increases, the wavelet extends including more time information, rather than greater detail. So, a low scale wavelet is a compressed wavelet, showing rapidly changing details, and thus corresponds to a high frequency ω . Inversely, a high scale wavelet is stretched and is associated with a low frequency ω . In the Morlet wavelet the scale is the distance between the oscillations. The period, or inverse frequency, is the approximate to the Fourier period, which corresponds to oscillations within the wavelets.

2.2.2.4 Wavelet power spectrum and phase

As already mentioned, the power spectrum of a time series describes how the variance of the data is distributed over the frequencies at which the time series can be decomposed. It is the power distribution, obtained by the wavelet coefficients τ, s , and is defined in equation 22 as the square of absolute-value of the wavelet coefficients, or the squared amplitude:

$$(WPS)_x(\tau, s) = |W_x(\tau, s)|^2 \quad (22)$$

This gives us a measure of the variance distribution of the time-series in the time-scale (or frequency) plane. This is usually represented in three axis: time (x), frequency (y) the frequency and amplitude over time (z). Typically, the charts show this third dimension through warm vs cold colours (red: high power, thus high volatility; and blue: low power, thus low volatility).

Wavelet phase

A complex wavelet function provides information about both the amplitude and the phase, which makes it more suitable to capture oscillatory behaviour. The Morlet wavelet considered is complex and therefore its CWT is also complex-valued. So, $W_x(\tau, s)$ can be separated into its real part, $\Re(W_x)$, and imaginary part, $\Im(W_x)$, or in its amplitude, $|W_x(\tau, s)|$, and phase angle $\phi_x(\tau, s)$. The phase angle is given by equation 23:

$$\phi_x(\tau, s) = \arctan\left(\frac{\Im(W_x(\tau, s))}{\Re(W_x(\tau, s))}\right) \quad (23)$$

With arctan denoting the extension of the usual principal component of the arctan function to four quadrants.

For real-valued wavelet functions, the imaginary part is zero and the phase is undefined (Torrence and Compo 1998). Therefore, to separate the phase and amplitude information of a time-series, it is necessary to use complex wavelets. The information on phase will be useful for the bivariate and multivariate analysis, when comparing two or more time series, thus allowing to observe if the series are in phase or out-of-phase.

2.2.2.5 Bivariate analysis with wavelets

In our study and many other applications, we are interested in detecting and quantifying relationships between two and more non-stationary time series.

The Fourier analysis also provides a useful analysis of relations in frequencies between time series. However, once again the independence of the temporal dimension in Fourier analysis does not allow a fruitful application of 'cross spectrum' concept to nonstationary series considered in this and other studies. CWT allows for an adaptation of concepts through the cross-wavelet power, cross-wavelet coherence and the wavelet phase-difference which enable us to deal with the time-frequency dependencies between two time-series.

Cross-wavelet transform and power

The cross-wavelet transform of time-series $x(t)$ and $y(t)$, $W_{xy}(\tau, s)$, is given by:

$$W_{xy}(\tau, s) = W_x(\tau, s)W_y^*(\tau, s) \quad (24)$$

The cross-wavelet power is simply given by $|W_{xy}(\tau, s)|$, showing the resemblance between each series power spectrum.

Phase-difference and wavelet coherence between series

For the analysis of the phase difference between different series, it is necessary to acknowledge the concept of wavelet coherence, in line with a similar concept used in Fourier analysis. Considering time series $x(t)$ and $y(t)$ it is possible to define their complex wavelet coherence, ρ_{xy} :

$$\rho_{xy}(\tau, s) = \frac{S(W_{xy}(\tau, s))}{\sqrt{S(|W_{xx}(\tau, s)|)S(|W_{yy}(\tau, s)|)}} \quad (25)$$

S is a smoothing operator in both time and scale. As in the Fourier case, smoothing is necessary, for otherwise the modulus of the coherence would be identically one.

The wavelet coherence, denoted by R_{xy} , is the absolute value of the complex wavelet coherence $\varrho_{xy}(\tau, s)$, presented in equation (26).

$$R_{xy}(\tau, s) = \frac{S(|W_{xy}(\tau, s)|)}{\sqrt{S(|W_{xx}(\tau, s)|)S(|W_{yy}(\tau, s)|)}} \quad (26)$$

The graphical representation of the wavelet coherence, $R_{xy}(\tau, s)$, at three dimensions, in line with the wavelet power spectrum, offers us a similar concept to the correlation between time series, but now also in the frequency domain.

The delays of the oscillations of the two series as a function of time and scale (frequency) may be obtained by the phase difference, $\phi_{x,y}(\tau, s)$, which is the angle of the complex wavelet coherence, ϱ_{xy} , defined in equation (27).

$$\phi_{x,y}(\tau, s) = \arctan\left(\frac{\Im(W_{xy}(\tau, s))}{\Re(W_{xy}(\tau, s))}\right) \quad (27)$$

Since ϱ_{xy} is a smoothed version of $W_{xy} = W_x W_y^*$, $\phi_{x,y}$ is very similar to $\phi_x - \phi_y$.

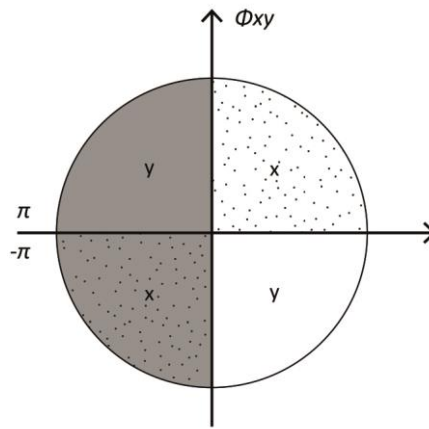


Figure 6 : Phase relations between time series x and y

(Grey quadrants: out-of-phase relation, white quadrants: in-phase relation; dotted quadrants: CO₂ leading, clear quadrants: CO₂ following.)

A phase-difference of zero indicates that the time series move in-phase at the specified frequency. On the contrary, anti-phase, at π (or $-\pi$) means that the move in opposite directions.

The time-series x is leading y when $\phi_{xy} \in (0, \frac{\pi}{2})$ and $\phi_{xy} \in (-\pi, -\frac{\pi}{2})$, while y is leading x for $\phi_{xy} \in (\frac{\pi}{2}, \pi)$ and $\phi_{xy} \in (-\frac{\pi}{2}, 0)$.

2.2.2.6 Multivariate analysis with wavelets

In the study of time series, including carbon and energy prices on which we focus in this work, it is necessary to consider the influence of one series in others. When working with more than two series, it makes sense to consider multiple and partial wavelet coherences. In this sense, it is possible to mirror the multivariate linear regression analysis to the multivariate study of the frequency spectrum (Priestley 1982). The concept of partial coherence exists when analysing the coherence between two variables, controlling for other variables. If this coherence decreases when controlling for other variables, then it can be considered that the coherence was due to the role of excluded variables.

The concepts of multiple and partial coherence developed by Aguiar-Conraria and Soares (2014) are generalizations for time-frequency of the corresponding concepts of multiple and partial correlation, in 'time', and the Fourier coherences, in 'frequency'.

Suppose we have three series x, y, z , we consider $\varrho_{xy.z}(\tau, s)$ the **complex partial wavelet coherence of x and y , after controlling for z** . We have:

$$\varrho_{xy.z}(\tau, s) = \left(\frac{\varrho_{xy} - \varrho_{xz}\varrho_{yz}^*}{\sqrt{(1 - R_{xz}^2)(1 - R_{yz}^2)}} \right) \quad (28)$$

The **partial wavelet coherence** $r_{xy.z}(\tau, s)$ is the absolute value of $\varrho_{xy.z}(\tau, s)$:

$$r_{xy.z}(\tau, s) = |\varrho_{xy.z}(\tau, s)| \quad (29)$$

Having defined the complex partial wavelet coherence $\varrho_{xy.z}$ between the series x and the series y , after removing the influence of z , the **partial phase-difference of x over y , given z** , is the angle of $\varrho_{xy.z}$. We denote this phase-difference by $\phi_{xy.z}$ and define it in equation (30).

$$\phi_{xy.z}(\tau, s) = \arctan \left(\frac{\Im(\varrho_{xy.z}(\tau, s))}{\Re(\varrho_{xy.z}(\tau, s))} \right) \quad (30)$$

2.2.2.7 Cone of influence and statistical significance

The Fourier transform assumes that the data is cyclic. In this sense, when analysing finite time series inevitable errors appear at the beginning and end of the wavelet power spectrum, called edge effects. A solution is to fill in the time series with zeroes before the transform and then remove them, as proposed by Torrence and Compo (1998). Additionally, larger scale represents a wavelet of greater length and therefore requires more zeroes to be added, which results in higher edge-effects. The cone-of-influence (COI) is, therefore, the region of the wavelet spectrum in which those effects exist, requiring a more careful interpretation.

For significance tests of the CWT, and considering that there are no duration issues for calculating, we fit an ARMA model to the series and construct new samples by drawing errors from a Gaussian distribution with a variance equal to that of the estimated error terms. For each time-series, or set, we perform the exercise 2000 times and extract critical values at 5% and 10% significance. However, following Ge (2008) we do not use significance testing for the phase difference. Alternatively, we only consider the phase information of the corresponding significant areas in the coherence analysis.

There are some theoretical distributions that could, alternatively, be used for significance testing for the wavelet power spectrum --- e.g. see Torrence and Compo (1998) concluded that the wavelet power spectrum of an AR(0) or AR(1) process is reasonably well approximated by a chi-squared distribution. Ge (2008), Cohen and Walden (2010) and Sheppard *et al.* (2012) have some important theoretical results on significance testing for the wavelet coherence. To our knowledge, no work has been done on significance testing for the partial coherence. However, the method of Sheppard *et al.* (2012) may probably be extended for this case.

3 DYNAMICS OF CARBON PRICES

3.1 Introduction

In an emissions cap-and-trade system, prices are the signal that guide the polluting companies' investments towards the use of cleaner fuels and energy efficiency.

Since the moment there is an obligation to comply with an emissions' limit, and trading is allowed, polluters need to have fast information of GHG pollution costs. Carbon prices are, thus, of major relevance to them. Besides, they are also required data for regulators to study and analyse the emissions market efficiency. This is visible in the theoretical analyses about the market's effectiveness and operational aspects that emerged even before the start of the European carbon market - EU ETS, (Hauch 2003, Huntington and Weyant 2004, Christiansen *et al.* 2005, Linares *et al.* 2006, Sijm *et al.* 2006, Smale *et al.* 2006). After, Zhang and Wei (2010) formalize the need for empirical studies of the EU ETS, regarding its operating mechanisms and economic effects. On mechanisms, price formation takes special concern, and the authors note it as necessary to the dynamic analysis of energy and carbon markets. Chevallier (2011a) complemented this work by reviewing the existing literature so far.

With the implementation of carbon markets, industries covered by the GHG market, such as electricity production, petroleum refining, glass, ceramics, and other energy intensive industries are the ones that need to understand carbon price variations, on a daily basis. For them, the carbon price is now necessary information to manage their portfolio optimization, production costs, and risk management in investment decisions (Roques *et al.* 2008, Fuss and Szolgayová 2010, Tolis and Rentizelas 2011). With the development of the market and higher liquidity levels, the consideration of the carbon price on those polluters' production decisions should increasingly be transmitted to their product prices. The importance of the information flow between energy markets and carbon markets is present in the research questions initially presented in this study. There, we state the expected influence of carbon prices in the prices of final and primary energies, and vice versa.

Under emissions limits, the power sector is the one that allows a more complete and meaningful analysis of the causes and effects of cap-and-trade. So, we now provide a brief description of this sector's features, relevant to our study.

In Europe, the power market is responsible for about one-third of GHG emissions from the combustion of fossil fuels, and so its facilities are naturally included in the carbon market. In this

context, the more mature and liquid the carbon market is, the more the price of electricity should consider the price of emission allowances. The same is expected to happen in the near future with the recent California market, where electricity production is responsible for 19% of emissions, including electricity imports, by energy source. In this sense, cost pass-through analyses have been made by Sijm *et al.* (2006), Zachmann and von Hirschhausen (2008), Sijm *et al.* (2012) and Jouvet and Solier (2013), concluding that there is information passing from carbon to electricity prices.

Another important feature is that the electric power supply is characterized by having to respond to different amounts of demand depending on the time of day, and by the impossibility of storage. This situation requires a decision on the use of producing plants known as the 'dispatch order', which corresponds to the decision about which plants to put in operation and when. The dispatch order varies for baseload generation, and peak-load generation. The baseload is the power demand quantity that has to be constantly provided. The peak corresponds to the hours of the day that need a greater generation effort (usually during the afternoon and early evening). Baseload powerplants are those that produce energy at a constant rate because they are not flexible to adapt output quantities, or, have higher shutdown and start-up costs. Usually they include nuclear and coal, which require hours, or days in the case of nuclear, to adjust the quantities produced. There are some renewables that can also support baseload supply, such as biomass, geothermal, or a small amount of hydropower. Power plants that quickly start operating are allocated to peak production such as gas or hydro power plants.

However, the management of gas and coal use is carefully attended by electrical producers, because of the difference in plants operation costs, in fuel prices, and now also because of carbon prices. In response to electrical producers need for indicators, the 'clean' spreads appear associated with indicators for coal or gas use in electricity generation: the Clean Spark Spread (CSS) and the Clean Dark Spread (CDS). The spreads refer to electricity sales margins over primary energy and correspondent allowances costs¹⁴. Through the CDS and the CSS it is easy to establish a switching carbon price, which indicates when switching between electricity generation from coal (cheaper, but more polluting) to gas (more expensive but less polluting) becomes advantageous. It is the carbon price that equals the CSS to the CDS, considering everything else

¹⁴ In electricity generation, coal is in proportion more polluting than natural gas (400 gCO₂/kWh with coal vs 780 gCO₂/kWh with gas) (IEA 2012). The CSS is the margin that a producer gets from the sale of electricity, having bought their needed units of gas and carbon allowances. The CDS is a similar measure, but for the production of electricity with coal.

constant (rate of efficiency of plants, prices of electricity and primary energy, etc)¹⁵. As an example, Abadie and Chamorro (2008) analyse the risk profile associated with the use of coal power plants, directly via CDS. Based on sectoral studies, Deng (2005), Näsäkkälä and Fleten (2005) and Laurikka and Koljonen (2006) conclude that in a market with emission limits, coal-fired power plants are facing financial risks originating on their profit margins, which in turn reduce their CDS, despite its cheaper fuel.

In short, energy prices and carbon related indicators, like the carbon switching price, represent how we measure the charge on polluters for their use of fossil fuels, via carbon markets. So, the investment and use of renewable sources may be called positive secondary effects in the current carbon markets goals. They are properly considered in complementary economy and policy measures, explicitly to promote these energy types. This argument is supported by Kumar *et al.* (2012) that does not find a significant relationship between carbon prices and the stock prices of clean energy firms. In Europe, the goal of reducing greenhouse gas emissions by 40% until 2030, is complemented with a parallel objective of increasing the proportion of energy consumed to 27% from renewable sources by 2030, “necessary to drive continued investment in the sector” EC (2014), p.1. In California the targets are similar, though not as ambitious: to the agreed limit to reduce emissions by 2020 to 1990 levels (about 15% reduction compared to the BAU scenario), various measures for energy efficiency and renewable generation are added, namely 33% renewable energy target by 2020.

The carbon market currently exists to control the use of fossil fuels, within the principles of diversity and security of supply in energy generation for the next 50 years.

Now, looking at carbon markets, as is being referred throughout this study, the European EU ETS and Californian AB32 carbon markets were selected for this research. The European market is the first major example of a GHG market. It is the largest, covering 45 % of emissions, more than 11,000 heavy energy-using installations in power generation and manufacturing industry, and oldest (since 2005). The EU ETS provides access to large amounts of data that reflect a developed emissions market. Such as in Europe, emission’s trading in California is a key element in fighting climate change. It now covers 35% of emissions from 600 facilities, and will reach 85% after 2015, which corresponds to 23% of the estimated reductions target. The California market

¹⁵ *Switching Price* = $\frac{\text{cost}(\text{gas})/\text{MWh} - \text{cost}(\text{coal})/\text{MWh}}{\text{tCO}_2(\text{coal})/\text{MWh} - \text{tCO}_2(\text{gas})/\text{MWh}}$

(AB32), existing since 2012, will most probably be one of the largest in the world in terms of participants' number, and associated emissions quantities. Also, this market is in many features related to the EU ETS. For these reasons and data availability, we included it in our study.

Research published at the time of the EU ETS inception, after 2005, is essentially focussed on the origins of variations in carbon prices and the explanation of the market operations. It is an understandable evidence, given the first system's youth. This research comprises aspects related mainly to price drivers and price formation (Mansanet-Bataller *et al.* 2007, Alberola *et al.* 2008, Seifert *et al.* 2008, Alberola *et al.* 2009b, Benz and Truck 2009, Blyth *et al.* 2009, Carmona *et al.* 2009, Daskalakis *et al.* 2009, Hintermann 2010, Chevallier 2011c, Creti *et al.* 2012, Gorenflo 2012, Aatola *et al.* 2013b, Lutz *et al.* 2013).

Studies multiply from 2007-2009 using data from the EU ETS first phase (2005-2007), i.e., the pre-Kyoto period, where Europe had yet to meet a UNFCCC threshold. Considerable efforts have been made since then to model the dynamics of the European carbon markets. The research diverged to several directions, including the study of the relation between carbon prices and features of market design (Alberola and Chevallier 2009, Alberola *et al.* 2009a), the relation with economic activity, the economic crisis and recovery (Christiansen *et al.* 2005, Bredin and Muckley 2011, Chevallier 2011c, Chevallier 2011d, Declercq *et al.* 2011, Durand-Lasserve *et al.* 2011, Creti *et al.* 2012), the connections to industrial activity (Reinaud 2007, Demailly and Quirion 2008, Alberola *et al.* 2009b, Hocaoglu and Karanfil 2011), the relation with prices of carbon offsets (Mansanet-Bataller *et al.* 2011, Nazifi 2013), and with levelling prices and clusters (Lanzi *et al.* 2012, Palao and Pardo 2012). Carbon prices volatility, risk-premia and forecasting have lately been the focus of attention, using mostly GARCH models, and relating several carbon financial assets (Benz and Truck 2009, Chevallier 2010, Chevallier and Sévi 2010, Chevallier 2011b, Feng *et al.* 2011, García-Martos *et al.* 2011, Arouri *et al.* 2012, Conrad *et al.* 2012, Feng *et al.* 2012, Rittler 2012, Aatola *et al.* 2013b, Byun and Cho 2013, Chevallier 2013, García-Martos *et al.* 2013, Liu and Chen 2013, Lutz *et al.* 2013, Zhu and Wei 2013, Koch 2014, Medina *et al.* 2014). Volatility spillovers are also analysed by Liu and Chen (2013) that uses a GARCH to analyses the impact of extreme weather in carbon and energy, and by Reboredo (2014) that looks to the relation between oil and the EU ETS using a multivariate range autoregressive model. On different methodologies, a copula approach has also been used to analyse value-at-risk of carbon prices (Gronwald *et al.* 2011, Li *et al.* 2013), the relation between carbon spot and futures (Zhuang 2013), and the relation to crude oil markets. Finally, Zhu *et al.* (2014) also investigate carbon futures variations using a Zipfian distribution.

All these studies, together, note the increasing maturity of the market.

Regarding the analysis of carbon price effects in other markets, particularly in the power market, studies are fewer in number (Reinaud 2007, Gulli 2008, Zachmann and von Hirschhausen 2008, Denny and O'Malley 2009, Oberndorfer 2009, Widerberg and Wråke 2009, Chen and Bunn 2010, Keppler and Cruciani 2010, Kim *et al.* 2010, Kury and Harrington 2010, Aatola *et al.* 2013a). Other studies by Hauch (2003), Kara *et al.* (2008), Fell (2010), Pinho and Madaleno (2011), Kirat and Ahamada (2011), Bonenti *et al.* (2013) and Thurber and Wolak (2013) are country-specific.

On the methodology, referred studies essentially explain the price or volatility of one variable in terms of others. This exogeneity assumption is very controversial in energy markets, so, to overcome this issue, we consider an approach that finds effects in both directions, between variables, regarding energy prices and carbon prices: a vector auto regressive (VAR) model, and tools of multivariate wavelet analysis (MWA).

Fezzi and Bunn (2009), Pinho and Madaleno (2011), Chevallier (2011d) and García-Martos *et al.* (2013) use VAR. Keppler and Mansanet-Bataller (2010) also consider multiple influence between variables, but through repeated standard unidirectional Granger causality tests. They consider daily data from 2005 to 2008, coal and gas prices, clean dark and spark spread and electricity prices. They also include temperatures as exogenous variables. Fezzi and Bunn (2009) build a vector error correction model (VECM) that analyses mutual relationships between electricity, gas and carbon prices in the daily spot markets in the United Kingdom, also regarding phase I of EU ETS. Chevallier (2011d) uses monthly data from 2005 to 2010 VAR Markov-Switching model, finding a connection between macroeconomics and carbon prices. Pinho and Madaleno (2011) examine interactions between carbon, electricity and fossil fuel returns on a country level energy-mix, as previously referred, through a VECM, using monthly data (2005/2009) in Europe. Finally, García-Martos *et al.* (2013) use daily data from 2009-2011, regarding fossil fuel prices, carbon, electricity prices, and offset prices, to build a conditionally heteroscedastic dynamic factor model. They compare prediction accuracy between a multivariate and univariate model, suggesting that the multivariate model improves the forecasting quality. Finally, previously referred Kumar *et al.* (2012) use a VAR to analyse stock prices of clean energy prices and carbon markets, and Chevallier (2011c) a factor augmented VAR to analyse shocks on carbon prices.

The use of vector auto regression models for time series analysis is customary in macroeconomics or finance research (Silvestrini and Veredas 2008), but not for the analysis of energy and carbon markets relation (García-Martos *et al.* 2013). Relevant references regarding vector auto regression time series modelling include Tiao and Tsay (1989), Enders (2008), Tsay (2010) and Peña *et al.* (2011), whose applications exist in large numbers, including to commodity markets (Geman 2009).

Regarding wavelet studies, they are indicative of existent relationships in other, longer, cycles than daily. Naturally, other authors, before us, have relied on wavelets to analyse the energy markets or the relation between energy prices and other financial or macroeconomic variables. Actually, one can argue that wavelet analysis is particularly well-suited for this purpose. Energy price dynamics are nonstationary and so it is important to use methods that do not require stationarity. Moreover, there is evidence showing that several energy markets display consistent nonlinear dependencies (Kyrtsou *et al.* 2009). Based on their analysis, the authors call for nonlinear methods to analyse the impact of oil shocks. Wavelet analysis is one such method. Aguiar-Conraria and Soares (2011b), Naccache (2011), Jammazi (2012) and Tiwari *et al.* (2013) have already relied on wavelets to study the evolution of oil prices, Aloui and Hkiri (2014) used the same tools to study the Gulf Corporation Council stock markets, and Reboredo and Rivera-Castro (2014) examine the relationship between oil and stock markets using wavelet analysis. Interestingly, Vacha and Barunik (2012) look to other energy commodities and find interesting dynamics of correlations between crude and heating oil, gasoline and natural gas. Vacha *et al.* (2013) rely on the wavelet coherence methodology to relate biofuels to several commodities (such as gasoline, diesel, corn, rapeseed oil, etc). To the best of our knowledge, specifically about carbon markets, there is no previous work in the time-frequency domain.

One common feature to all the above cited papers is that they rely on uni and bivariate wavelet analysis. So far, multivariate wavelet analysis has never been applied to economic data. This is an important shortcoming, because when the association between two series is to be assessed, it is often important to account for the interaction with the other series. To estimate the interdependence, in the time-frequency domain, between two variables after eliminating the effect of other variables, we will rely on the concept of partial wavelet coherence and partial phase-difference.

In our research, we consider daily data of phase II and III of the European carbon market and the pre-start and first stage of the market in California. We removed the values of phase I of the EU ETS (2005-2007) from the European study, although available, because they refer to the pre-Kyoto period. At that time, not only the EU had not yet mandatory emission limits, as the polluters realization of an oversupply of allowances in 2006 led to a drop in prices to values near '0' until the end of this period. Sufficient data from more mature phases of the market is available, so we chose to disregard EU ETS phase I information. We include carbon *spot* prices in this study because they are a better mirror of daily expectations regarding variations of remaining energy

prices (Alberola and Chevallier 2009, Daskalakis *et al.* 2009). Those remaining energy prices, described in sections 3.2.2 and 3.3.2, were selected as the most indicative of European and Californian realities. We also included an index of economic performance and the daily average temperatures, the latter as a proxy for variations in demand.

On the methodology, as mentioned, our study extends the previous work by Fezzi and Bunn (2009), Chevallier (2011d) and García-Martos *et al.* (2013), also encompassing the work by Keppler and Mansanet-Bataller (2010), for a more comprehensive analysis of the interactions of energy and carbon markets. We capture multivariate interaction between variables through a VAR model and analyse the data in a time-frequency dimension, through multivariate wavelet analysis.

In section 3.2 we analyse the EU market and in 3.3 Californian market.

3.2 Part I – Europe: EU ETS

Based on papers:

“Dynamics of CO₂ price drivers”

“Carbon Financial Markets: a time-frequency analysis of CO₂ prices”

3.2.1 EU ETS main features

The Kyoto Protocol is a contract ratified by several industrialized countries that imposes a limit on their greenhouse gas (GHG) emissions. It also provides three flexibility mechanisms to help countries to reach their goal. Those mechanisms are the Clean Development Mechanism (CDM), Joint Implementation (JI) and Emissions Trading. The first two regard project instruments, where it is possible to obtain emission certificates by developing mitigation projects. The third mechanism, Emissions Trading, distributes emission permits by countries, known as Assigned Amount Units (AAUs) and allows them to exchange those permits in order to fulfil the predetermined carbon cap. In theory, emission markets allocate reduction efforts where they are least expensive.

The Kyoto Protocol also allows for the implementation of regional emission trading schemes, like the European Union Emission Trading Scheme (EU ETS). In this market the trading unit is the European Union Allowance (EUA), developed to be a fungible¹⁶ unit with the AAUs from the Kyoto countries trading scheme. The EU ETS is operational since 2005: 2005-2007 was called Phase I, a test phase, while Phase II, 2008-2012, was a binding phase for it was at the same time the Kyoto Protocol commitment period, in which European countries had to internationally fulfil Kyoto obligations. 2013-2020 is the third phase, and in this period, with the new EU ETS Directive, and Climate and Energy Package (Directive 2009/29/EC), the rules changed substantially. The market has now a wider scope with the introduction of new gases and new sectors. The inclusion of the aviation sector in the EU ETS brings new policy possibilities, since it falls within a sector of transport activity, not included in the Kyoto Protocol. Finally, it is important

¹⁶ Fungibility is an asset's property that allows it to be exchanged with other individual asset of the same type. In Kyoto particular case, EUAs may serve as AAUs when it comes to the country's compliance.

for carbon prices' analysis to note that another novelty in the 3rd phase was that the total quantity of emission in the EU is determined at Community level, and allowances are mostly allocated through auctions.

More recently, on 22/01/2014, the European Commission presented to the European Parliament the "2030 climate and energy goals for a competitive, secure and low-carbon EU economy" (EC 2014). The EC proposal has six key energy-climate elements, including the reduction in GHG emissions by 40% below the 1990 level and the reform of the EU ETS. Regarding changes in the EU ETS, the EC (2014), p.1 *"proposes to establish a market stability reserve [...] that would both address the surplus of emission allowances that has built up in recent years and improve the system's resilience to major shocks by automatically adjusting the supply of allowances to be auctioned"*.

However, even with all the referred changes in market features, and constant new climate policy goals, the EU ETS market principals have remained the same. And after almost 9 years of EU ETS, it is possible to say that unreasonably low carbon prices and their causes are the main concerns for keeping the market operational while actually reducing GHG emissions.

Briefly recalling the existing research presented in section 3.1, several authors have studied aspects of carbon prices formation usually using EU ETS carbon data, most of them after the end of Phase I, the test phase. Granger causality tests have been the most common methodology for interconnection analysis between CO₂ prices and other variables. Furthermore, previous analyses usually only consider a one-way influence of variables related to CO₂. More recent studies have focussed on volatility analysis and high frequency prices suggesting the use of GARCH models (Aatola *et al.* 2013b, Byun and Cho 2013, García-Martos *et al.* 2013, Lutz *et al.* 2013, Koch 2014, Medina *et al.* 2014). Others use VAR models to detect and overcome the endogeneity problem and estimate the impact of innovations with respect to other variables (Gorenflo 2012, Kumar *et al.* 2012, Aatola *et al.* 2013b).

Focussing on studies that look at the origins of variations in carbon price, relevant research confirm the impact of the variation of industrial production in EUA price changes (Alberola *et al.* 2009a), and that the relationship between the carbon price and the economy is robust to the introduction of energy market shocks (Chevallier 2011d). Keppler and Mansanet-Bataller (2010) and Aatola *et al.* (2013b) show that electricity prices Granger-caused CO₂ prices. Keppler and Mansanet-Bataller (2010) also find significance in the causality from gas price to carbon. Aatola *et al.* (2013b) finds a relationship between coal prices with the carbon price in 2005-2010. And

finally, Lutz *et al.* (2013) conclude that the most important EUA price drivers are changes on the stock market and coal, gas and oil prices.

On carbon and energy prices effects, the results are not as many as in the carbon price drivers: Fezzi and Bunn (2009), Mansanet-Bataller *et al.* (2007) find that both carbon and gas prices drive electricity prices. Kirat and Ahamada (2011) find evidence of carbon prices influence in electricity prices in Germany and France. (Pinho and Madaleno 2011) also study origins and effects of carbon and energy prices at a country level.

Looking at data from 2008-2013¹⁷, in this section we aim to characterize CO₂ prices interrelation with the most relevant energy, economy, substitute goods and weather variables influencing this market. First we specify a dynamic vector auto-regressive (VAR) model, which is usually used to analyse and display interdependencies between different time series. With this model, we can estimate response functions of CO₂ prices to impulses in other variables. These impulse-response functions (IRF) allow us to observe the impact of other variables in CO₂, in terms of duration, direction and magnitude. We also use with data from the Kyoto commitment period, when companies and countries had international obligations to reduce emissions, as they still have now. Secondly we present the results of the multivariate wavelet analysis to estimate the long run coherence between variables.

3.2.2 Selected data

Controlling for GHG emissions through markets implies that emissions are limited, have a price and may be exchanged. The emissions limit is the fixed emissions allowances supply. Therefore, in this market, the expected price drivers for emission allowances will include main emitters' activity, and variables that affect their production. That is to say energy prices, economic activity and variations in the demand. Considering the previous idea, and taking into account previous work on CO₂ price causality (Alberola *et al.* 2009a, Fezzi and Bunn 2009, Keppler and Mansanet-Bataller 2010, Sijm *et al.* 2012, Aatola *et al.* 2013b, Lutz *et al.* 2013, Nazifi 2013) our model considers eight variables: CO₂ price, Certified Emission Reduction (CER) price, base and peak electricity price (Elect_b and Elect_p), gas and coal prices (Gas and Coal), average temperature (that

¹⁷ We do not include information from Phase I of the EU ETS because it was not a compliance period, as it was almost a 'test' phase. Given the price break that occurred under those specific conditions, there is a high possibility that the data would bring noise to our analysis.

provides a proxy for days with higher energy demand) and a European economy stock market index (Econ). Variables as the Clean Spark Spread, the Clean Dark Spread or the «carbon switch» were not considered because they are linear combinations of variables already included.

In Figure 7, we can see the emission data variables in levels. As in Figure 8, regarding energy prices, one can observe the abrupt decline between mid-2008 until mid-2009, due essentially to external economy conditions. After one year and a half recovery, it is visible a slower but constant deterioration in prices.

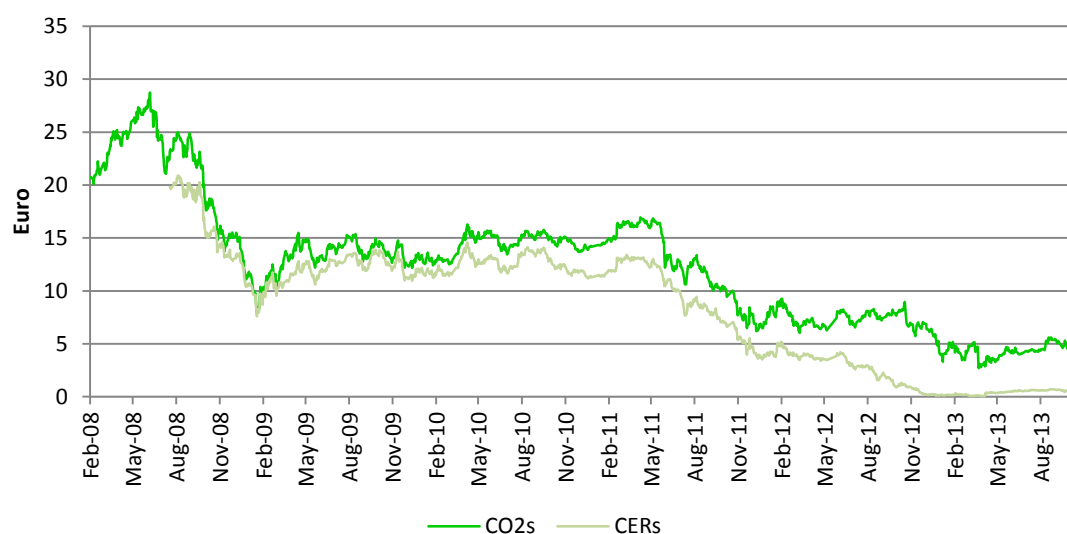


Figure 7 : EU carbon prices, 2008/2013.

CO₂

The European Union Emissions Trading System (EU ETS) is the first and the largest international system for trading greenhouse gas emission allowances. 2008-2013 is the time length of this study representing EU ETS Phase II (2008/2012) and one year of Phase III (2013-2020). Considering this, as CO₂ variable we used the European Union Allowance (EUA) spot price, the unit of the EU ETS, referring to the emission of one tonne of CO₂ equivalent. EUA future prices were not included because of spot-future high correlation level (99%).

Data for CO₂ was available from 2008/02/26 up to 2012/11/01, from Bluenext, the most important EUA spot market in volumes, then. Although Bluenext closed permanently its spot and derivatives trading operations as from December 5, 2012, the environmental trading exchange

has hosted the largest amount of spot trades, totalling 29.4 million tons in 2012¹⁸. From Nov-2012 until 12/11/2013 prices were collected from SendeCO₂¹⁹. There is data missing from around 40 days, which did not prove to be of any concern, given the almost 5 years of daily data available.

Certified Emission Reductions (CERs)

Installations covered by the EU ETS have the possibility to accomplish their emission targets surrendering Certified Emission Reductions (CERs), in addition to EUAs. A CER is an emission unit concerning reductions within the Clean Development Mechanism (CDM), a market-mechanism under the Kyoto Protocol. Within this mechanism, emission reductions are issued from mitigation projects in least developed, and developing countries that ratified the Protocol. The market supply of CERs is controlled by the Executive Board to the CDM that evaluates those projects. CERs are then traded in secondary markets.

Although there is currently a political debate on the role of CERs because of the continuous price fall since 2012, Phase II market rules accepted CERs as partial substitutes for EUAs. This rule has been maintained in post-Kyoto phase. . The price spread between EUAs and CERs was of high importance at least until 2012 (Nazifi 2013). For this reason we considered its spot daily price in this study. Data was gathered from Bluenext for after 12/8/2008. From Nov-2012 until 12/11/2013 prices were collected from SendeCO₂. Minor missing data did not pose a problem.

Energy

Prices of EU energy variables included in this study are presented in Figure 8. Greenhouse gas emissions considered in the European carbon market come from fossil fuels burning and follow a top-down accounting methodology. In the end, more than 11000 power stations, industrial plants and airlines, in Europe, operate under GHG emission limits. Hence, energy markets have an expected importance in the variations of CO₂ price, and, because of this, energy prices were considered in our model. We included typical prices for natural gas, coal and electricity in Europe as energy variables. For all, one month future contract was selected. This choice is in line with

¹⁸ In <http://www.bloomberg.com/news/2012-10-26/bluenext-carbon-exchange-to-shut-after-losing-eu-auction-bid-1-.html> , retrieved 11/03/2012.

¹⁹ www.sendeco2.com , Iberian carbon emission stock exchange, retrieved 15/11/2013.

the established notion that, in energy, future prices lead spot prices essentially due to the difficulty of storage, and consequent ease of shorting.

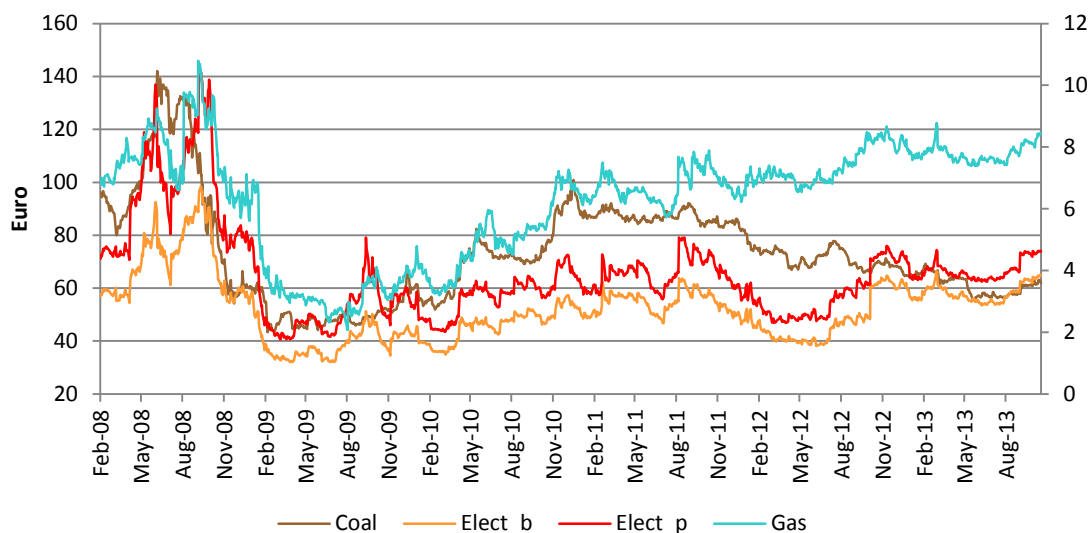


Figure 8 : EU selected energy prices, 2008/2013.

(On the left vertical axis we refer to electricity and oil prices. The right axis refers to gas and coal prices. Data sources: referred in text.)

Regarding natural gas prices we used The Intercontinental Exchange Futures²⁰ (The ICE) data. Originally in £/therm, the data was transformed to Euros/MMBTU for compatibility with other variables and better perception²¹. As for coal one month future prices, they were also retrieved from The ICE database. Coal prices are cost, insurance and freight (CIF) with delivery in Amsterdam, Rotterdam and Antwerp (ARA). They were originally in USD/tcoal and were converted to EUR/tcoal. For electricity, the Phelix baseload and peak prices²² were retrieved from the European Energy Exchange (EEX)²³, in Euros/MWh. Baseload and peak prices reflect different electricity generation mixes and thus are relevant in our analysis. The Phelix prices regard the German/Austrian market area. They were selected as representatives of the European base and

²⁰ We thank The ICE from providing us the data for natural gas and coal used in this paper.

²¹ Historical exchange rates available at the European Central Bank website: www.ecb.int.

²² Because electricity needs are not constant all through the day, and it is a non-storable good, we considered two typical electricity prices: peak, that represent prices for a time of day when supply is significantly higher than average levels, and base, an average for the rest of the day.

²³ We thank EEX for providing the data on electricity prices used in this paper.

peak electricity prices since Germany is the largest electricity producer in Europe, which combined with Austria reached 680TWh²⁴ of generated electricity in 2011²⁵. Also, correlation levels between Phelix data and other electricity prices (tested for France and UK) range from 0,87 to 0,95. So, variations presented through Phelix prices should appropriately represent variations in other European electricity prices, in spite of aspects such as market structure and energy-mix. Finally, there are almost no gaps in energy prices (only 14 days missing data).

Economic activity

Noting that industries involved in the EU ETS are energy intensive, and thus their production levels are highly associated with general economic growth, we considered necessary the inclusion of a variable which mirrored economic activity. This is in line with several previous authors in the subject (Alberola and Chevallier 2009, Chevallier 2009, Keppler and Mansanet-Bataller 2010). For this purpose we considered the FTS Eurofirst 300 Index (E3X.L), available at YahooFinance. It is a capitalization-weighted price tradable index measuring the performance of Europe's largest 300 companies. Daily price returns were included, and there is no missing data.

Weather

Average daily European temperatures were considered in this study. They were calculated based on the average daily temperatures from regions of 7 representative EU countries (Austria, Germany, France, Italy, Netherlands, Spain and United Kingdom), retrieved from the European Climate Assessment & Dataset²⁶. It is a weighted average considering the population of each region²⁷. The result is a European average daily temperature index, which was included in the model as the only *a priori* exogenous variable. Data is available until 30/09/2013. For consideration of global warming effects, temperature would have to be endogenous. However, this aspect would only be relevant if we had data for several decades, which is not the case.

²⁴ BP Statistical Review of World Energy 2012 www.bp.com/statisticalreview

²⁵ Regarding market power structure, the German market is relatively non-concentrated, when comparing to other EU electricity markets Scheepers, M., Wals, A. and Rijkers, F. (2003). *Position of large power producers in electricity markets of north Western Europe*. Draft Rep. ECN-C-03-003, Amsterdam, The Netherlands., although large mergers around 2005 have increased vertical market concentration Domanico, F. (2007). *Concentration in the European electricity industry: The internal market as solution?* Energy Policy **35**(10): 5064-5076..

²⁶ European Climate Assessment & Dataset [official page: eca.knmi.nl](http://eca.knmi.nl)

²⁷ Following the methodology used by Tendances Carbone for the European Temperature Index www.cdcclimat.com/-Tendances-Carbone-.html

3.2.3 VAR analysis

The initial VAR system model with log differenced variables may be written in a compact form that includes a set of linear dynamic equations, one for each variable. Each equation is specified as a function of its past values, and equal number of past values of all other variables. The final goal is to estimate how CO₂ responds to impulses in other variables, and vice versa.

We have seven endogenous variables and one exogenous variable, the average temperatures. The seven endogenous variables include representative prices of CO₂, CERs, peak and base electricity, gas, coal, and an economy stock index. To account for non-stationarity issues, all variables were transformed to first differences of log data. Stationarity of these time series was established by typical tests. We rely on likelihood ratio test statistic to decide on the number of significant lags to include in the VAR model. The test points towards the consideration of 21 days/lags, corresponding roughly to one month of daily data.

3.2.3.1 Causality and feed-back relations

A central question in VAR models is the endogeneity or exogeneity of variables, as discussed in the previous section. In this study, temperature was the only variable considered exogenous *a priori*. For all other variables, we ran Granger causality/block exogeneity tests to perceive if any variable should be treated as exogenous. In these tests, a χ^2 Wald statistics is given for each equation for the joint significance of each other lagged endogenous variables in the equation, as well as a statistic for joint significance. The results are described below in Figure 9.

As we may see in Figure 9, we found interdependencies in several variables, and some recurring influence cycles. Recall that the purpose of the Wald test is not to quantify any relation, but instead to identify multiple relations. This analysis allows surpassing the problem of missing variables, present in bivariate causality tests. Additionally, looking at the results of individual and joint significance of lagged endogenous variables, there is no variable that should be considered exogenous in this model.

Regarding CO₂, its returns are significantly caused by the economy returns, peak/base electricity price returns and CERs prices. Fezzi and Bunn (2009) and Mansanet-Bataller et al. (2007) find a direct influence of gas and coal prices in CO₂ prices, but in our model those influences are captured through the electricity price. It is also worthwhile to note some indirect channels. For example, gas influences both peak and base electricity, which in turn influences economic activity,

which causes CO₂. Therefore, even if we do not find a direct influence running from gas and coal prices to CO₂ prices, we do find indirect linkages.

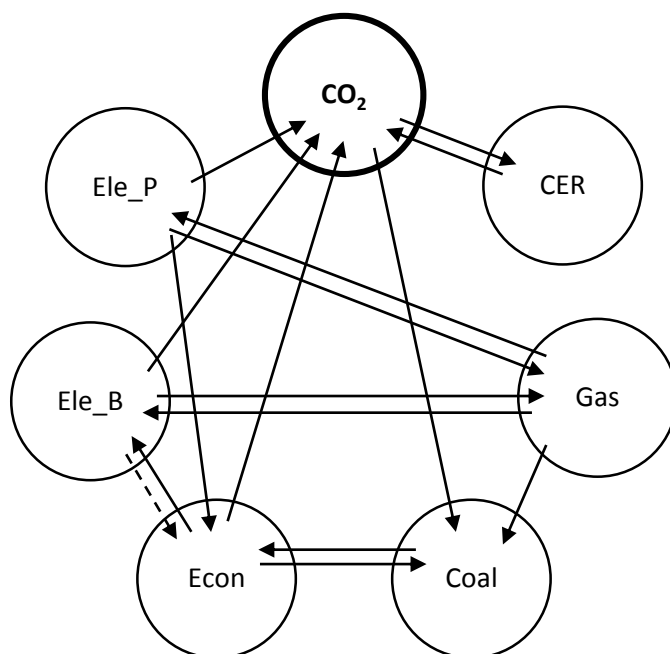


Figure 9 : EU prices - Granger causality tests

Data: 02/01/2008 - 30-09-2013. Dashed/continuous arrows indicate causality at 10%/5% significance.

In the case of peak electricity, gas price has significant explanatory power, a result in line with the findings of Fezzi and Bunn (2009). This is an adequate result given that natural gas is an important primary energy for thermal electricity production. Natural gas has a lower GHG emission intensity (469gCO₂/kWh²⁸), and more flexible supply, when comparing to coal. In this model gas and peak (and base) electricity returns have a feedback effect meaning that past values of each one influence both contemporaneous values. This is also an acceptable result given that utilities define their generation mix looking at past values of electricity and primary energy prices. In the particular case of the electricity prices considered, one should note that the energy mix for power generation associated with the Phelix price is intensive in coal (lignite and hard

²⁸ Moomaw, W. et al, 2011, "Annex II: Methodology. In IPCC: Special Report on Renewable Energy Sources and Climate Change Mitigation" (ref. page 10), http://srren.ipcc-wg3.de/report/IPCC_SRREN_Annex_II.pdf , retrieved 18/03/2013

coal are important fuels). Its effects are being transmitted through the gas price, as we will see below in Figure 15 and Figure 16.

Regarding energy variables we only found evidence for a significant influence of CO₂ in coal returns, in 2008-2013. To some extent this result follows the current general opinion that carbon prices are too low to have an impact on electricity prices.

Finally, the economy, gas and CO₂ price returns influence coal price returns. This last result could benefit from further study, given the very high emission intensity levels (1001gCO₂/kWh²⁸) of electricity generation with coal. However it is an aspect that falls out of this study main purpose, and so we leave it for further developments.

3.2.3.2 Impulse-response analyses

As discussed earlier, it is necessary to choose a Cholesky ordering of the variables for the contemporaneous impact. We considered gas being influenced only by its own innovation, then coal to have its own and be influenced by the gas innovation, then peak electricity, following the same reasoning having its own innovation, and the ones from coal and gas, after, base electricity, then the economy, CO₂, and finally CERs. This choice reflects carbon market price principles by which it captures influences of industrial output levels, effects of mitigation actions, and economic circumstances. Also, it follows suggestions in Granger causality tests presented above. In the end, this particular ordering is not important as our results revealed to be robust to different orderings.

Variance decomposition

The Cholesky order is also needed when calculating the variance decomposition. This is auxiliary evidence of the amount of the forecast error variance of each variable that can be explained by innovations in other variables. That is saying, how much each variable contributes to each other in the model. Below, in Figure 10, we present the variance decomposition of carbon and electricity (other variance decompositions are available in the appendix section A.3).

In the CO₂ graph (a) we may observe the growing importance of other variables over the carbon price itself. In the baseload electricity graph (b), the most important variable is the peak electricity price (in red). In the first periods there is a growth in the importance of gas over peak electricity, but, globally, the role of all other variables remain rather constant.

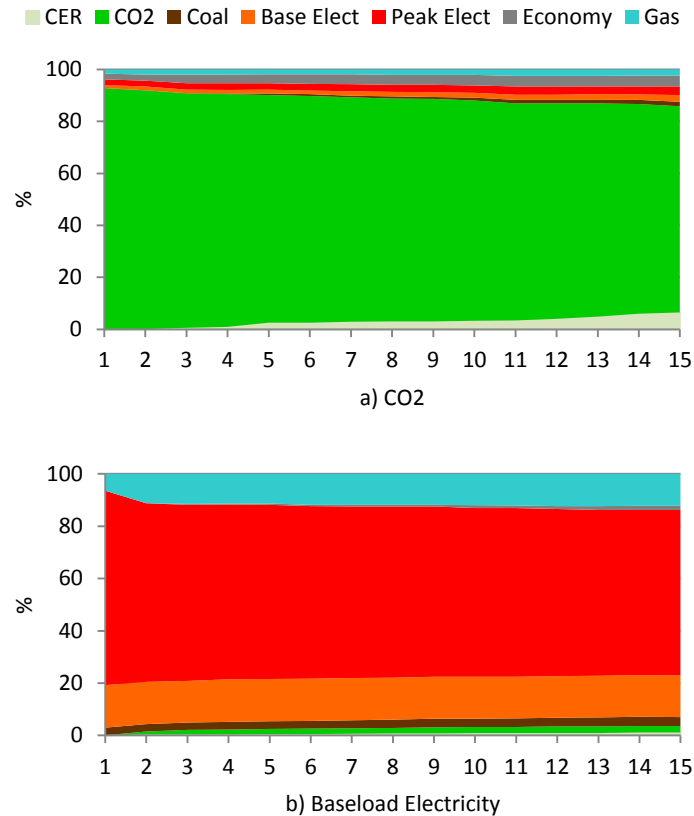


Figure 10 : Variance decomposition of carbon and electricity prices - EU

However, our main purpose is to look to the effects in carbon prices, when having a shock in other variables, or, to the effects in other prices, when having a shock in carbon. These can be seen through impulse-response functions.

There are 49 (7×7 variables) IRF in this model. It would be purposeless to show them all. We find relevance to look at the influence of carbon prices in primary and secondary energy prices, for these results would sustain market fundamentals. Recalling the goal of this study to analyse CO₂ responses to shocks in other variables it is also of interest to analyse the effect in carbon prices of energy prices, emission permits substitutes prices, and the economy. We will first look to the seven IRF that show this.

CO₂ response functions

For IRF display we selected the accumulated responses because variables are in first log differences, so the interpretation should be clearer. We also tested for several response periods, and 10 days revealed to be enough to show the response asymptote to a non-zero constant.

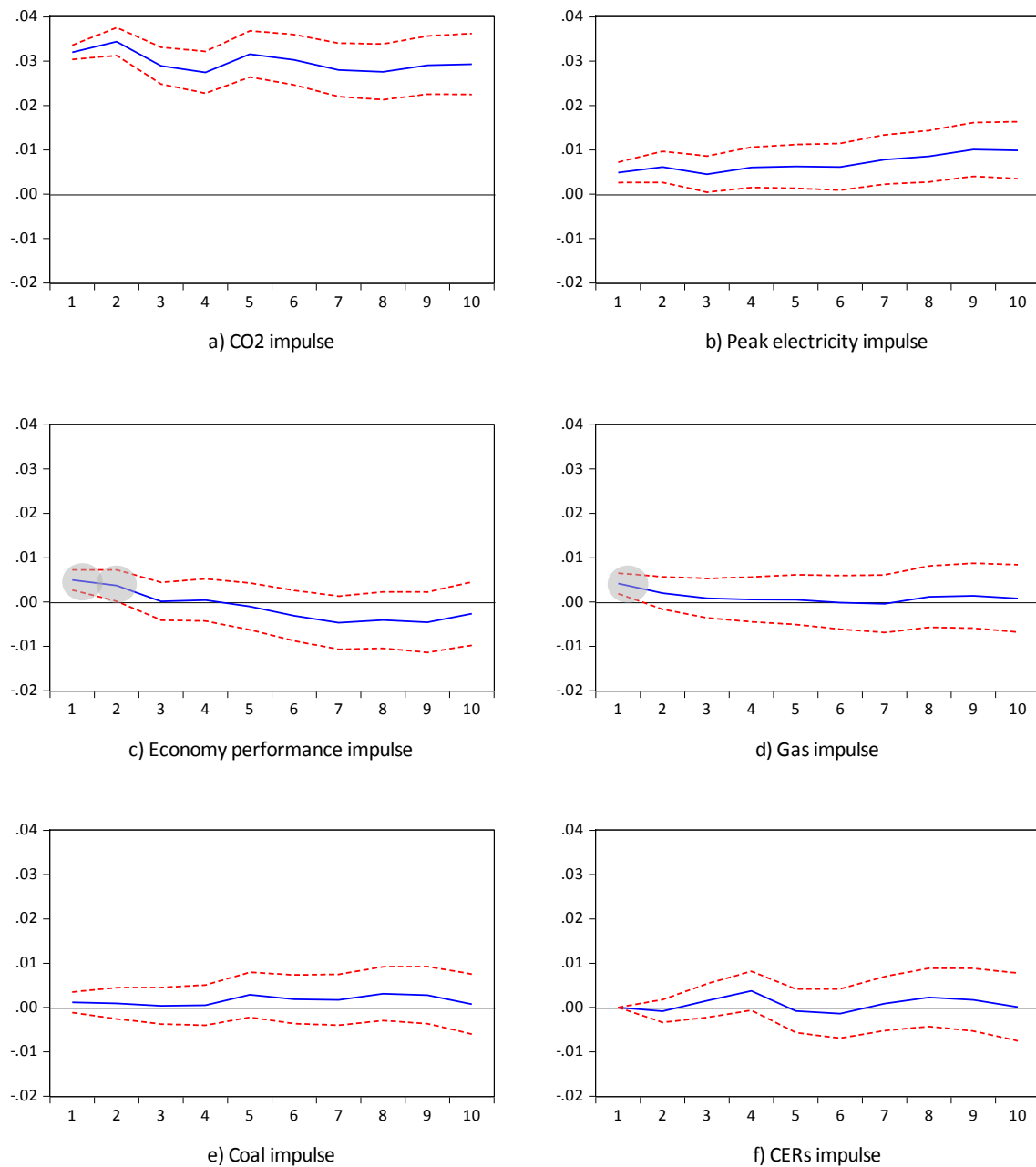


Figure 11 : CO2 price returns accumulated responses to impulses in other variables - EU

(Blue line is the IRF; red dashed lines the limits of the 95% confidence interval. Grey circles indicate significance, whenever the function has both significative and non-significative values.)

Figure 11 above represents the accumulated response of CO₂ price returns to one standard deviation innovation of gas, coal, peak electricity, economy, CO₂, CER, +/- 2 standard errors.

In Figure 11 a), we see that the impact of CO₂ innovations on itself is always positive and significant. After two days this impact almost stabilizes, and then, though still positive, it slows down in the 6th to the 7th day, only to start rising again and stabilizing. Because these are accumulated

responses, it is possible to see that an impulse from CO₂ will positively change CO₂ returns and that this change will endure, which was an expected result.

In Figure 11 b) we may see the response of CO₂ price returns to an innovation in peak electricity price returns. The impact is significant in all periods and increasingly positive. Globally this is also an expected result, for electricity generation emits a large part of the CO₂ considered in the market. So, if there is a positive change in peak electricity prices variation, it is expected that CO₂ prices variation will act accordingly. There is a visible response in the next 10 days, and in the end the change in CO₂ price levels will sustain.

Regarding the role of the economy, in Figure 11 c), the contemporaneous and the 2nd day impact in CO₂ returns is positive. That is saying that economy and emissions move in the same direction. This is the third expected result of this study: as CO₂ emissions origin is energy intensive production, and this production is known to be highly related with economy levels, it is expected that a positive change in the economy returns has a positive response from CO₂ returns. The novelty is that this impact is transitory, significant only in the first two days.

Looking at natural gas, we see a marginally significant positive impact in CO₂ returns, in the first period. After the second day the results are not significant. This result from the natural gas shock is in line the findings of Fezzi and Bunn (2009), and consistent with the definitions of *Clean Dark and Spark Spreads* that analysts and utilities consider in their decisions for the generation mix. As referred in the data description section, these spreads are linear combinations of electricity, carbon, coal and gas prices, displaying the most cost-efficient option for electricity generation in one period, either using coal or gas power plants. What we show in this result is that changes in the natural gas prices are immediately considered in the carbon price variation.

Finally, in Figure 11 f), changes in certified emission reductions prices, or CER, associated with clean development mitigation projects in developing and least developed countries, have no immediate impact in CO₂ price changes. It is an important result that CER price changes had no expected impact in the European carbon market during 2008-2013²⁹, confirming Mansanet-Bataller *et al.* (2011) previous results regarding EUA-CER spread.

²⁹ However, the CDM market is undergoing a phase with over-registration of projects, which caused CER prices to start falling since the beginning of 2012. In 2013 they reached the lowest levels ever recorded. Knowing this, emitters started to buy swaps CER-EUA derivatives for they have an immediate profit margin in buying CERs and selling EUAs. This event may be reflected in the next few years in the EUA carbon price, and then a change in the presented IRF function may be expected.

A final result is that significant impacts from CO₂ and peak electricity price returns don't fade overtime. This means that whatever impact in CO₂ a shock from these variables has; it will withstand in future periods.

CO₂ impulses

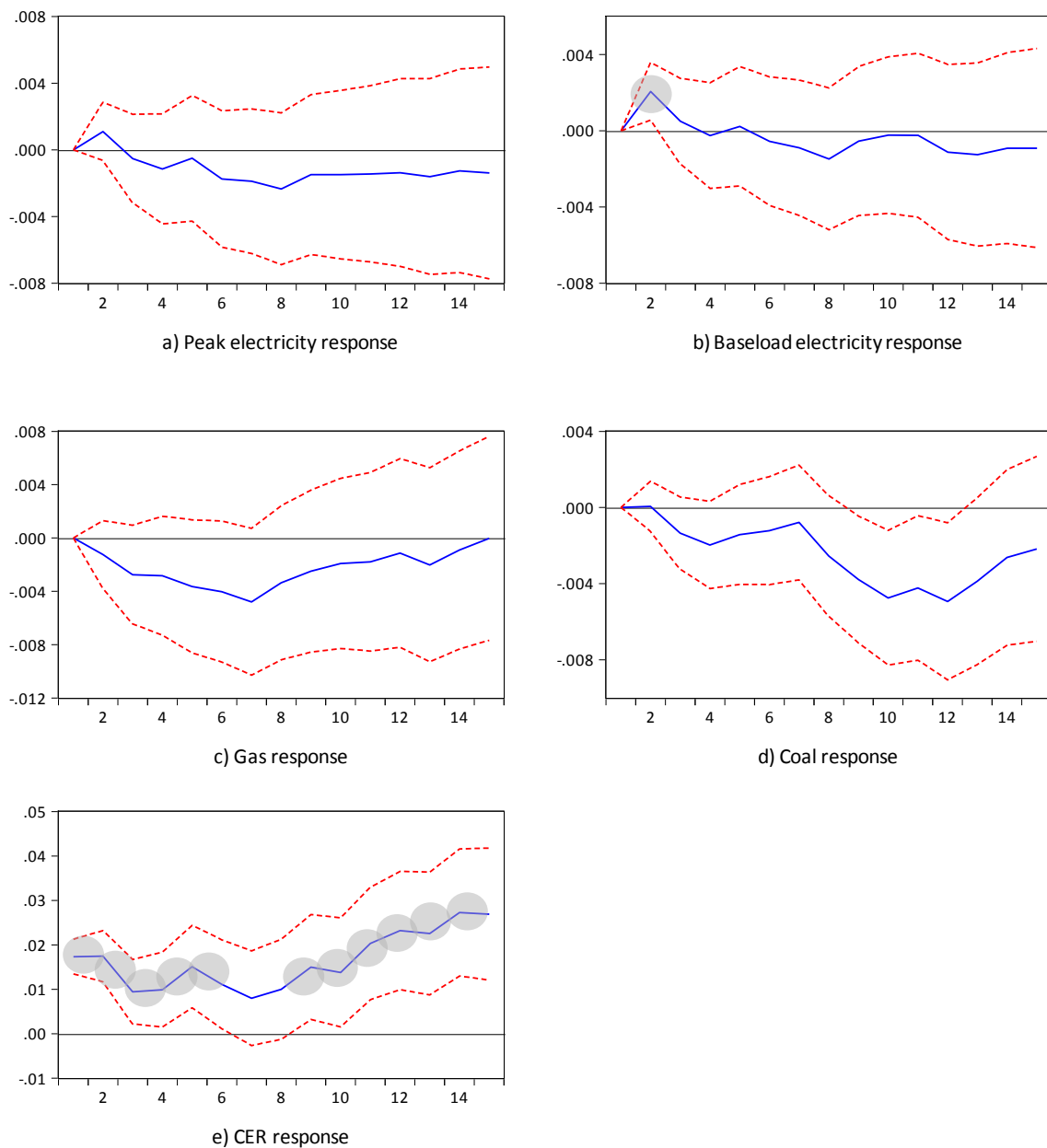


Figure 12 : Impulses in CO₂ prices and accumulated responses of selected EU prices

(Blue line is the IRF; red dashed lines the limits of the 95% confidence interval. Grey circles indicate significance, whenever the function has both significant and non-significant values.)

Once more, accumulated responses were selected, and 10 days response period was considered for the same reasons. In Figure 12 above we represent the second view in the interaction between carbon and energy prices. It shows the accumulated response of all variables to one standard deviation innovation of CO₂, +/- 2 standard errors.

Following emission markets fundamentals we should anticipate a positive and possibly larger impact of CO₂ in the most polluting variables. However a significant impact is only visible in two variables: base electricity (b) and CERs (d).

On base electricity (Figure 12 b) the CO₂ impact is almost negligible. It is only significant at day 2 and shows positive but very low values, becoming insignificant afterwards. This means that a positive change in CO₂ returns causes a positive change in base electricity returns. There being no direct influence of CO₂ on primary energy price returns (coal c) and gas d)), it is expected that an impact, however small, may be visible in the base electricity variable. This final energy comes from thermal power plants, emitters of GHG (except for nuclear, not included in emission markets), whereas peak electricity energy-mix is composed of non-polluting renewable energy (hydro) and a small percentage of gas-fired plants. In this sense, looking at the minimal positive impact on base electricity returns, we may consider that CO₂ price is on the right path for influencing GHG emissions, although lacking in magnitude.

On CERs, there is a significant, yet small, positive impact from EUAs returns, the data representing CO₂ variable. This is visible in almost all 10 periods, and continues in the future. As observed in the previous section of CO₂ responses, this confirms previous results where EUA-CER have a positive one direction relation, only from EUA to CER, because the European carbon market is the largest source of CER demand (Mansanet-Bataller *et al.* 2011). The spread between the two prices increased on a large scale mainly due to the large fall in CERs prices (visible in Figure 7)

Other impulse-response functions, cycles and feedback

The five graphs in Figure 13 provide us with additional evidence on transmission mechanisms of information between different prices, also known as cost pass-through information. We tested situations previously proposed by the Granger causality analysis (Figure 9).

We may see that the responses are mostly significant, and positive, with the exception of the gas response to the baseload electricity impulse. Although this relation is not very easy to explain, we may say that gas prices are responding negatively to rises in the baseload electricity price, to compensate coal's lower prices.

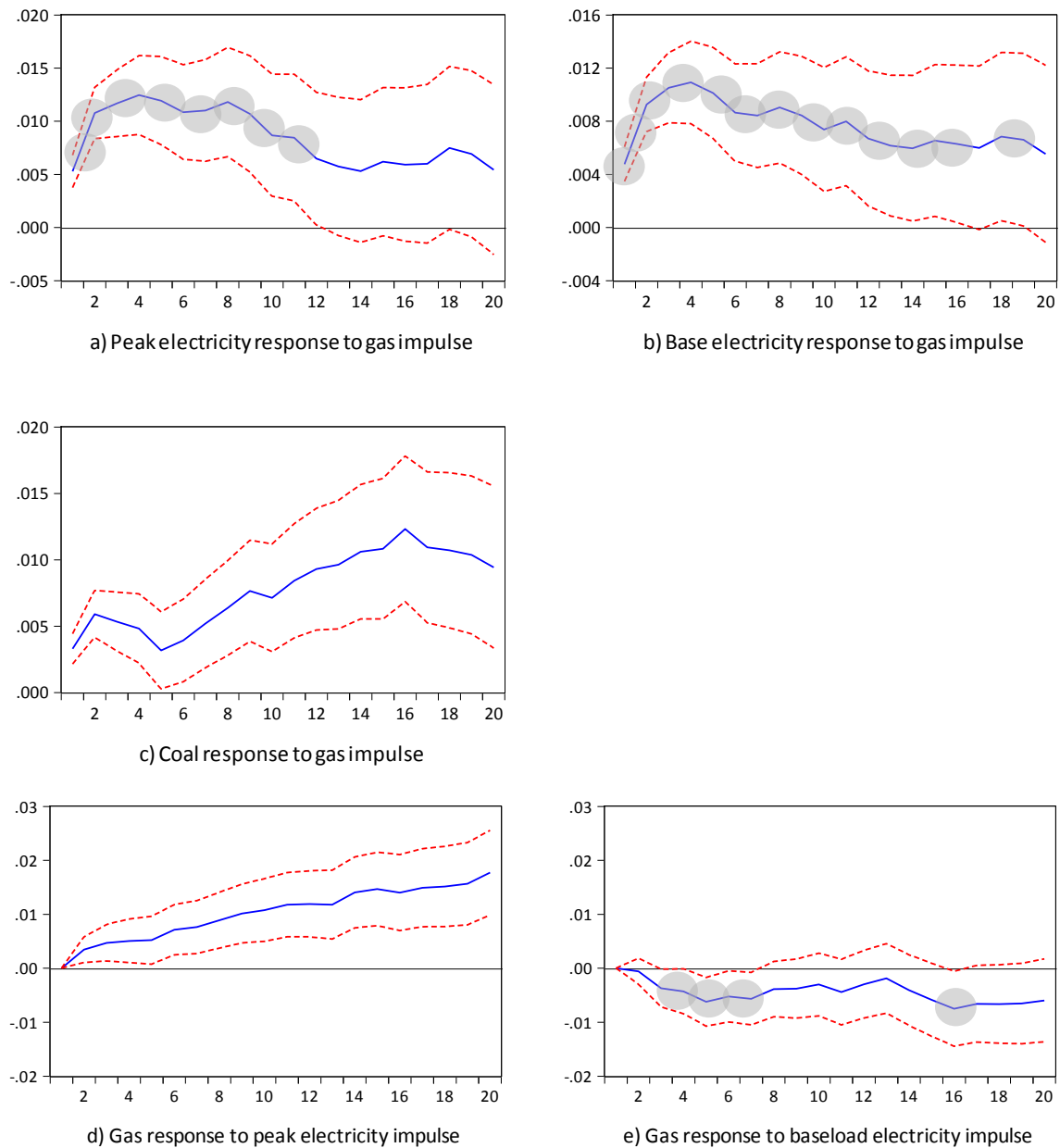


Figure 13 : Other accumulated impulse-response functions of energy prices - EU

(Blue line is the IRF; red dashed lines the limits of the 95% confidence interval. Grey circles indicate significance, whenever the function has both significant and non-significant values.)

The graphical representation of causality provided in the VAR model on Figure 9, is particularly interesting when checking for cycles of influence between different variables, such as the one mentioned before. We briefly present the significant cycles found between variables, validated by impulse-response functions (of Figure 11, Figure 12, Figure 13):

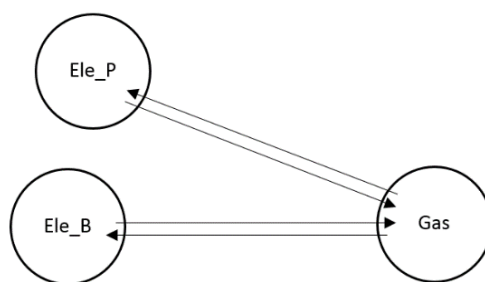


Figure 14 : Causality cycles between electricity and gas prices - EU

Among others, it is possible to identify the following sequences in Granger causality analysis in the EU market that support the result that primary energies only affect the carbon market indirectly via final energy prices (electricity prices). In Figure 15 we observe the role of coal and its relation to CO₂, and in Figure 16 we include the gas price in the analysis.

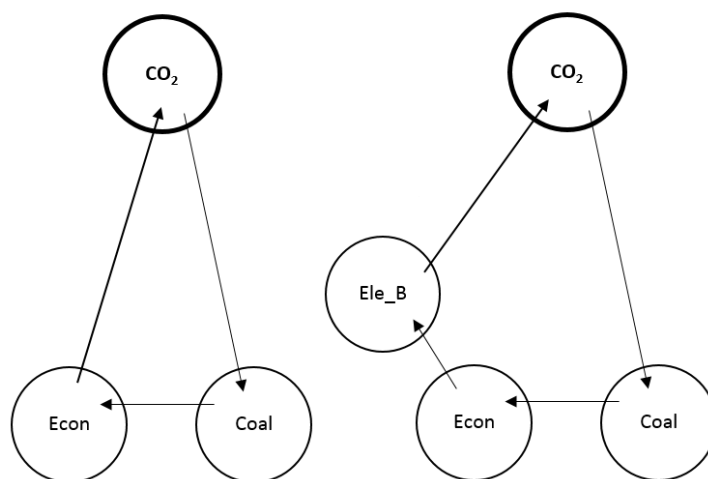


Figure 15 : Other causality cycles: the role of coal – EU

On the role of the economy, we find rebound effects regarding this variable, arguing (Chevallier 2011d), although via an indirect path. However, we agree that this relation is robust to shocks in other variables (Hintermann 2010, Chevallier 2011d).

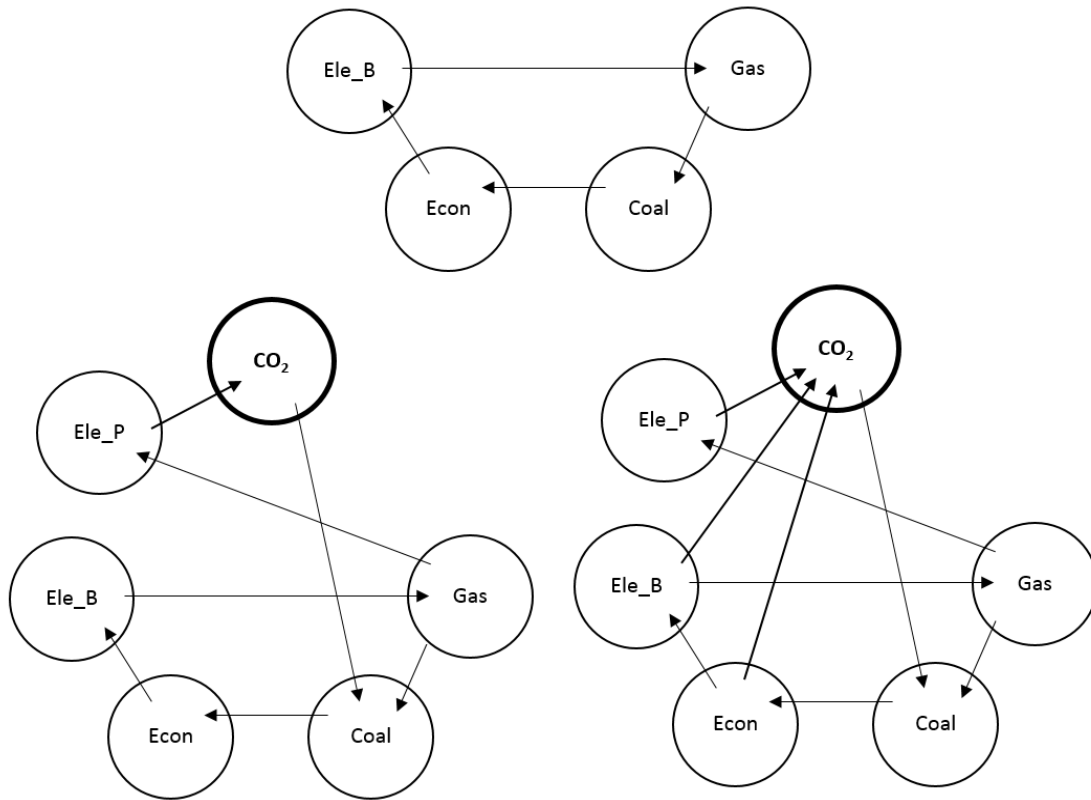


Figure 16 : Other causality cycles: the role of gas - EU

There are other cycles present in the Granger causality analysis, but our study is focussed on the carbon relations, which we study with thorough detail, so we leave it for other analysis of energy markets.

3.2.4 Wavelets analysis

The variables for this analysis are depicted in Figure 17, left-hand-side panel, together with their wavelet power spectrum. They include carbon, gas, coal, electricity and the economy. CERs were not considered because of the recent downfall in the CDM market. Expected results of this variable would never be sufficiently important to justify the additional computation needed.

The wavelet power indicates, for each moment of time the intensity of the variance of the time-series for each frequency of cyclical oscillations. This provides a first assessment of the behaviour of each variable in the time-frequency domain.

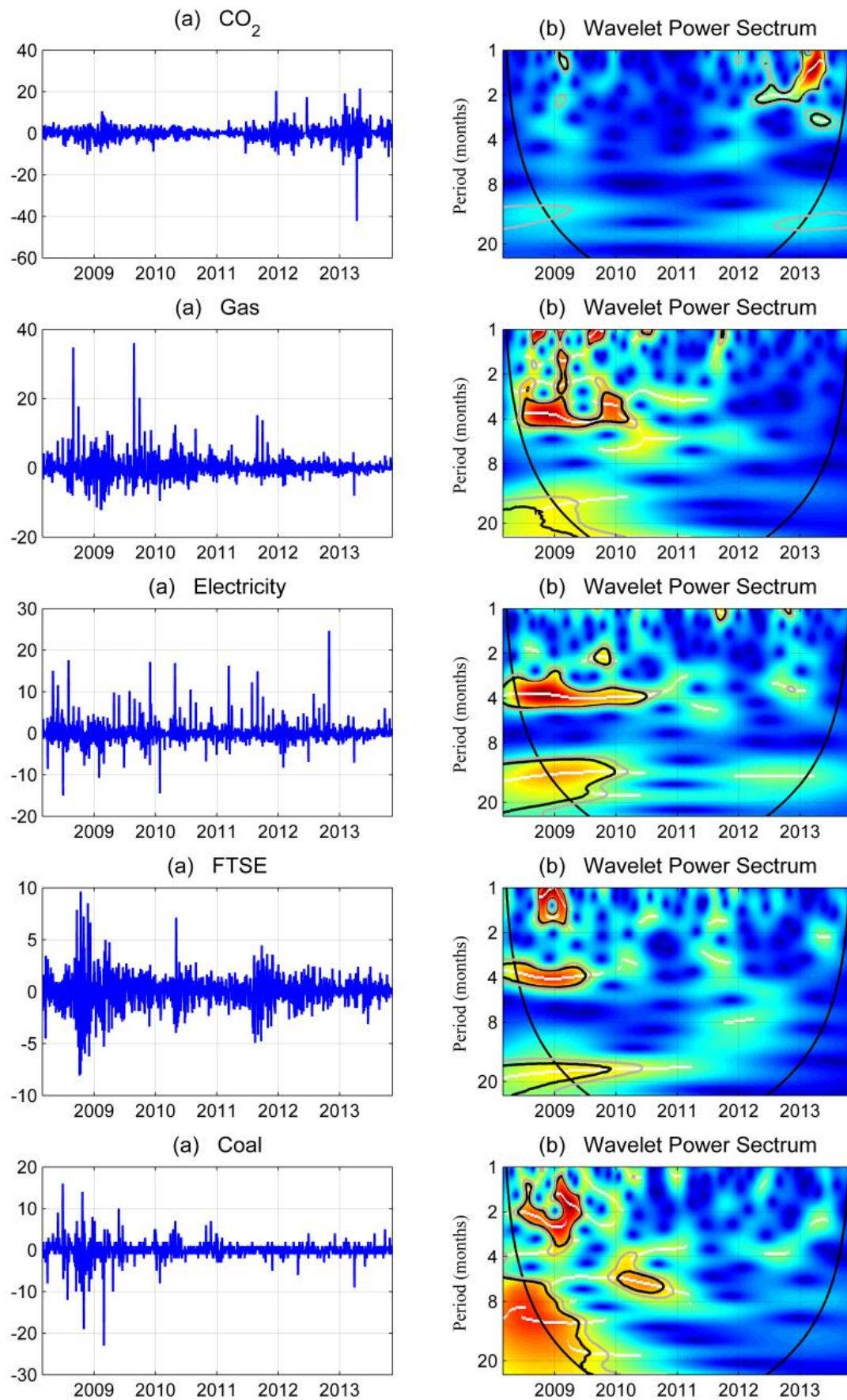


Figure 17 : EU prices - time-series plot and time-series wavelet power spectrum

(The black/grey contour designates the 5%/10% significance level. The cone of influence, which indicates the region affected by edge effects, is shown with a black line. The color code for power ranges from blue (low power) to red (high power). The white lines show the maxima of the undulations of the wavelet power spectrum.)

Looking at Figure 17, it is interesting to note that the market for CO₂ is much less volatile than the other markets. Additionally, the periods of high volatility do not coincide. While markets for gas, electricity, coal and FTSE exhibit high levels of volatility until 2010, especially at 4 months frequencies (and also at longer run cycles, such as cycles with a periodicity of 20 months). Volatility in the CO₂ market is only apparent after 2012 and, especially, during 2013, at very high frequencies. Based on the wavelet power spectra is difficult to discern any inter-relations between these markets.

As we said before, we use daily price returns for each variable of interest. While the price levels seem to follow a unit root, the daily returns exhibit no unit root, both according the traditional ADF and KPSS unit root tests, or a more robust wavelet based unit root test (Fan and Gençay 2010).

We performed two more tests. First, for every variable, with the exception of the daily returns of CO₂, we tested and rejected the null of no serial correlation using a multi-scale test for serial correlation proposed by Gencay and Signori (2012). Then we estimated Hurst coefficients and found them very close to zero. This means that while the daily returns show some linear dependency they do not show any discernible long-range dependency. We also estimated an ARMA model with GARCH errors, to deal with the linear dependency and time evolving variance, as several others have done with financial data. However, even after doing so, the hypothesis that the standardized residuals follow a white noise is severely rejected. We tested this latter hypothesis using the BDS statistic (Broock *et al.* 1996) and the null was rejected in every single case. This suggests that some non-linearities are robust to this traditional modelling and provides one more reason to rely on wavelet analysis.

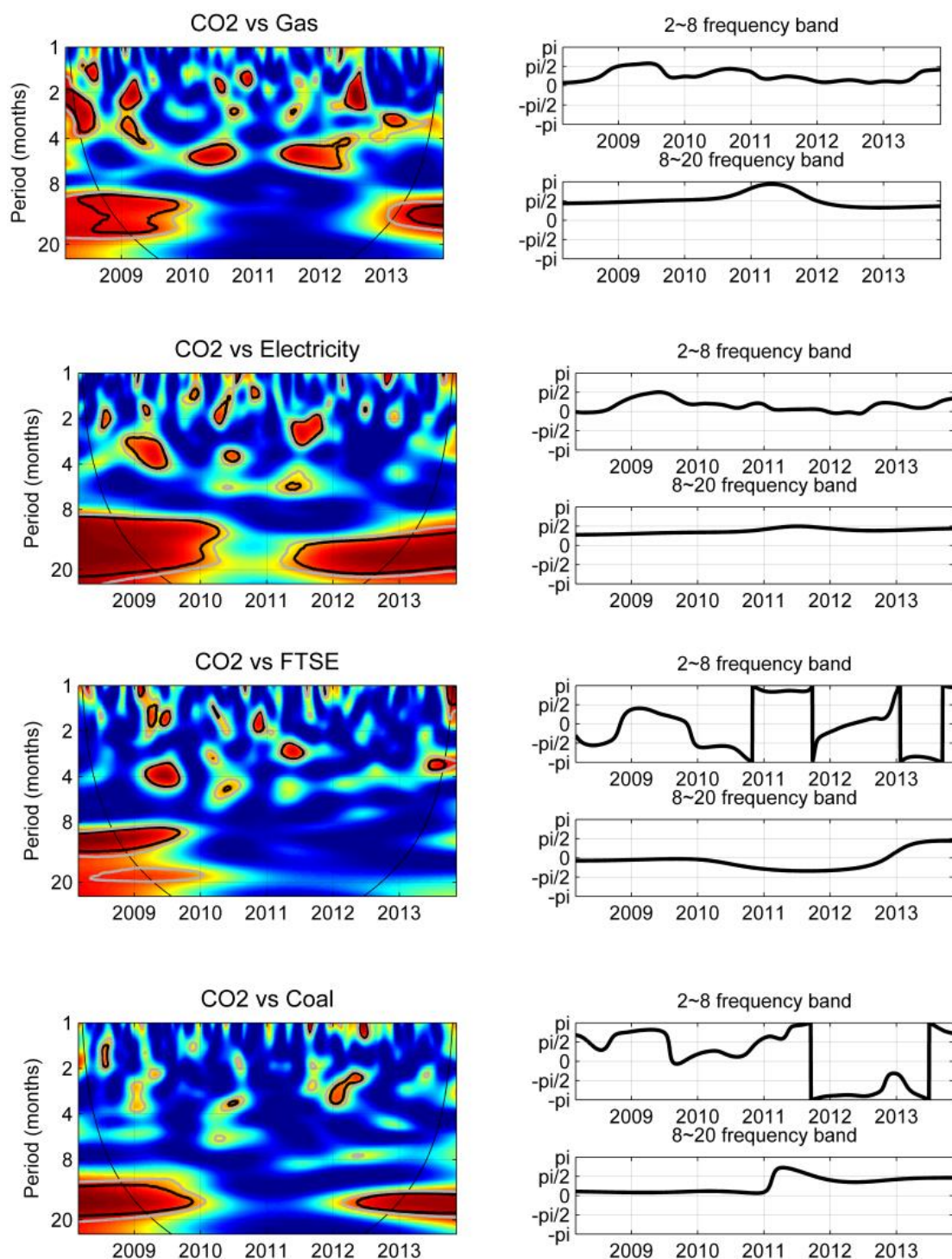


Figure 18 : EU prices - wavelet coherence and phase-differences

(On the left we find the wavelet coherence. The thick/thin black contour designates the 5%/10% significance level. The color code for coherence ranges from blue (low coherence --- close to zero) to red (high coherence --- close to one). On the right we represent the phase-differences between CO2 and another variable (top: 2~8 frequency band, bottom : 8~20 frequency band)).

In Figure 18, we estimate the coherence between CO₂ and other variables. It is interesting to note that before 2010, at longer run frequencies (corresponding to cycles of periodicity between 8 and 20 months) we observe a statistically significant coherence. Looking at the phase-difference, and focusing in particular in the 8~20 frequency band, we observe very stable lead-lag relationships³⁰. Between CO₂ and the energy variables the phase-difference is typically between 0 and $\pi/2$, indicating that the variables are in phase (positive correlation), with CO₂ leading. Between CO₂ and FTSE we see that the phase-difference is very close to zero, indicating an almost simultaneous relationship. If anything, the phase difference is slightly negative, suggesting that the lead variable is FTSE.

The relations described in the previous paragraph should not be taken as much more than descriptive statistics. In fact, when more than two series are given and the association between two of them is to be assessed, it is important to account for the interaction with the other series, otherwise one risks incurring an omitted variable bias. To estimate the interdependence, in the time-frequency domain, between two variables after eliminating the effect of other variables, we rely on the concepts of partial coherence and partial phase-difference, described in the previous section.

In Figure 19, we have the partial coherence between CO₂ and each of the other variables, after controlling for all the others.

Comparing Figure 18 with Figure 19, we see that the results change somewhat and that not considering the partial coherence would lead us to erroneous conclusions. First, the relation between CO₂ and gas is almost nonexistent, once we control for the other variables. The other two variables that reflect energy markets exhibit quite different dynamics.

On the one hand, the region of (statistically significant) high partial coherence between CO₂ and Electricity is situated in the 8~20 frequency band and is observable across most of the sample. For that frequency range, the partial phase-difference is consistently between 0 and $\pi/2$, which shows that the series move in-phase, with CO₂ leading.

³⁰ It is difficult to attach any meaning to the phase-difference in regions where coherence is not statistically significant. Therefore, we refrain from interpreting the phase-differences at the shorter run frequencies.

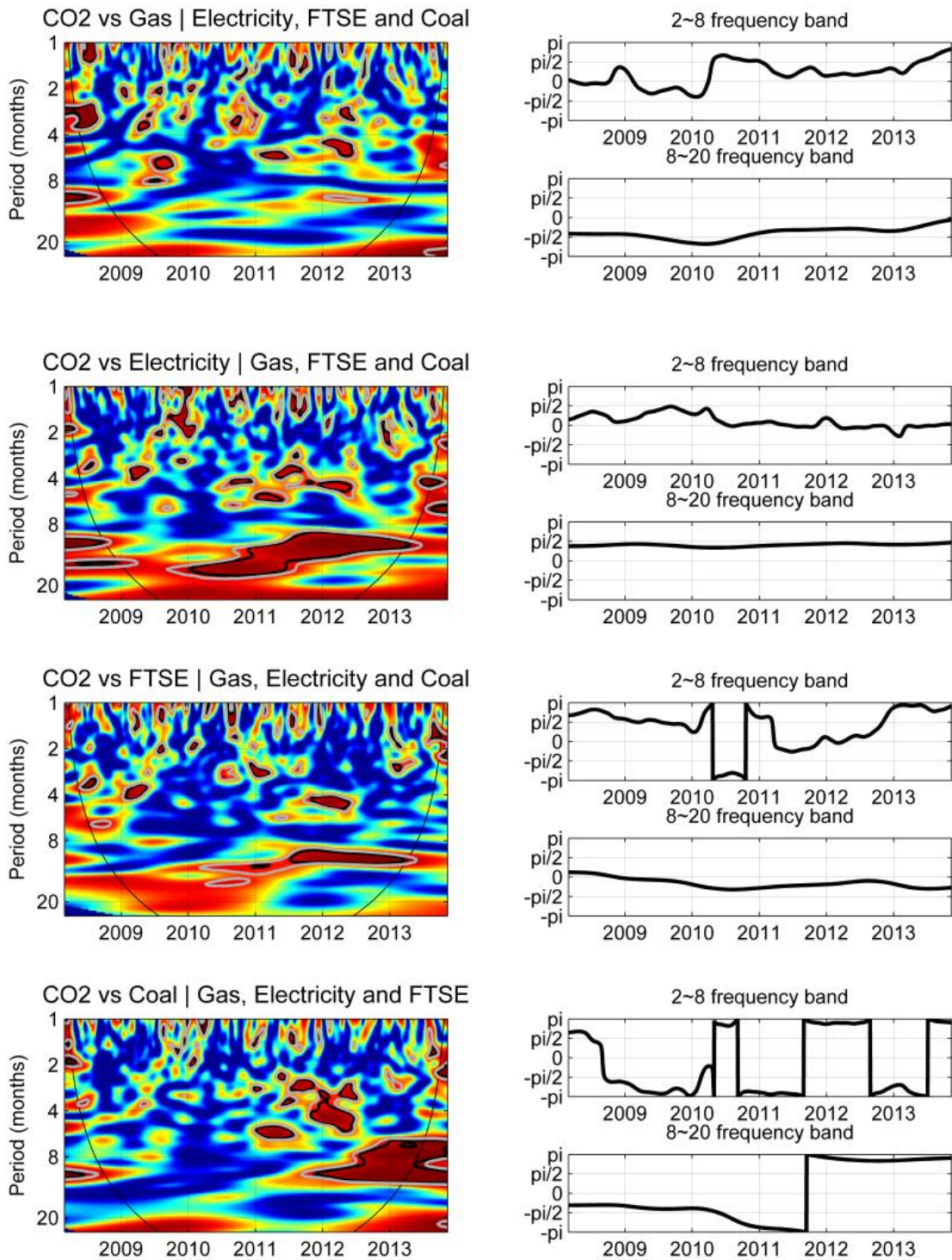


Figure 19 : EU prices - partial wavelet coherence and partial phase-differences

(On the left we find partial wavelet coherence. The thick/thin black contour designates the 5%/10% significance level. The color code for coherence ranges from blue (low coherence --- close to zero) to red (high coherence --- close to one). On the right the partial phase-differences between CO2 and the other variable are represented (Top: 2~8 frequency band. Bottom : 8~20 frequency band))

On the other hand, partial coherence between CO₂ and Coal is stronger after 2011, especially after 2012. It is also interesting to note that this relation is also clearly visible at higher frequencies. Moreover, the partial phase-difference is very close to π at the lower frequency band and it switches between $-\pi$ and π at higher frequencies. This shows that the variables are almost perfectly out-of-phase and that, if anything, coal is the lead variable along the 8~20 frequency band.

Finally, the partial coherence between CO₂ and economic activity, measured by FTSE, is particularly stronger between late 2011 and early 2013, especially for cycles with periodicities slightly above 8 months. In this time-frequency range, the partial phase-difference is between $-\pi/2$ and 0 suggesting that the variables are in-phase with CO₂ lagging or following FTSE.

3.2.5 EU ETS synthesis of results

In this section we aimed at characterizing the relation between CO₂ prices and energy prices, certified emission reduction prices and economy index prices. We estimated a VAR model considering all variables endogenous. We included temperatures as the only exogenous variable. Daily data from Phase II and one year of Phase III (2008-2013) of the EU ETS was used.³¹

Regarding effects on CO₂ price returns, we found significant effects from electricity price returns and the economy index. This supports the idea that main power utilities could have influenced CO₂ price in 2008-2013. When we consider a positive impulse in variables our results suggest a positive response of CO₂ returns in all cases except for CER and coal. Looking at the other variables, an impulse of electricity price had a 10 days impact in CO₂ returns, and of gas a 1 day impact. The economy had 2 days impact. Finally, CO₂ returns also had a 10 days impact in itself. In the opposite perspective, CO₂ returns have a very small one day impact in base electricity price returns, and a consistent effect in CERs variable.

No evidence was found of CO₂ influence in primary energy variables but only in base electricity price returns.

On the wavelet analysis, we observed several situations relating carbon prices to energy prices that are consistent with a growing maturity of the European carbon market. We found evidence

³¹ Restricting our analysis to 2008-2012 would yield similar results.

that, in cycles between 8 and 20 months, CO₂ and electricity variables are correlated, with CO₂ leading, contributing to the accomplishment of the main objective of the market, which is to penalize emissions from emitting energy use.

Surprisingly we do not find a significant relation between CO₂ and gas in the longer time-cycles referred. Instead, we observed a high partial coherence between CO₂ and electricity, with CO₂ leading, and between CO₂ and coal, with coal leading. This result suggests that carbon pricing is having effects in the final good, electricity, instead of on primary fuels, gas and coal. It seems that power suppliers are passing on the emission cost of using coal in their generation mix to the consumers through the electricity price. This is consistent with a low price demand elasticity of this good.

We also find higher volatility in carbon prices only after 2012, which may relate to the political uncertainties over the third phase of the market, starting in 2013. At the same time, we observe that the carbon price follows the economy trends, in line with previous studies.

With the results presented, namely the in-phase relations of CO₂ with electricity prices around a 12 months cycle, CO₂ leading, and of the economy with CO₂, in the same frequency band, with the economy leading, regulators should consider that the intended effects of the carbon market are present, even if only in longer cycles.

Also, results show us that there is no evidence that penalizing CO₂ emissions depleted economic activity in the time frame considered, controlling for final and primary energy variables. When the relation between carbon and the economy is significant, from mid-2011 almost until the end of our sample data, both variables move in phase, with the economy leading. In short, in our data frame, carbon prices are related with energy prices, and they follow the economy tendencies.

It is important to note that this study was conducted using data from 2008 to 2013, in Europe, meaning that the current economic and financial crisis has possibly influenced our results. This is one main reason why we included the Californian market in this study, a market with different operation and accounting methodologies and economic conditions. Further policy implications of our results in the EU ETS are referred in the discussion in chapter 4.

To conclude, the idea that carbon prices are capturing coal and gas price information and reflecting it in electricity prices, allow us to say that the EU ETS is reaching stability, operating towards the right goal. However, we suggest tackling the need to overcome the recognized oversupply of allowances, in order to allow for CO₂ prices to directly influence primary energy prices, and incite further emissions reductions.

3.3 Part II – California: AB32

Based on papers:

“California Carbon Allowances Price Drivers - First Evidences”

“CO2 price dynamics in Californian Carbon Financial Markets”

3.3.1 AB32 main features

First microeconomic computer simulations of cap-and-trade systems for cities and their emissions were designed by Burton and Sanjour between 1967 and 1970 (Burton and Sanjour 1970, Burton *et al.* 1973) for the US National Air Pollution Control Administration (now called the US Environmental Protection Agency's Office of Air and Radiation - EPA). In subsequent years the first “cap-and-trade” system was implemented, under the Clean Air Act, as part of the US Acid Rain Program. “Acid rain”³² was mainly caused by sulfur dioxide and nitrogen oxides, from fossil fuel-burning power plants, especially coal power plants. The cap-and-trade system was conceived by C. Boyden Gray, and trading started in 1995. Results show that the initial limit or ‘cap’ goal was reached in 2007, almost three years before the deadline, and at one fourth of the initially expected costs (EPA 2007, Napolitano *et al.* 2007).

After this first example, in the last 20 years, carbon markets have become officially implemented in international trade. In the USA, carbon trading proposals have not yet been taken up at the federal level, although the Waxman-Markey bill came close. Nevertheless, state action on carbon markets continued, including the launch of the Regional Greenhouse Gas Initiative (RGGI)³³, a trading system for emissions of power generators that started in 2009, aiming to reduce greenhouse gas (GHG) pollution by 10 % by 2018 based in 2009. RGGI encompasses nine Northeastern US states and all obligations for power plants with more than 25 MW of installed capacity.

³² <http://www.epa.gov/airmarkt/progsregs/arp/>

³³ Regional Greenhouse Gas Initiative: <http://www.rggi.org/>

The Western Regional Climate Action Initiative³⁴ (WRCI), 2007, formed by seven Western US states and four Canadian provinces, arises from the confluence of the West Coast Global Warming Initiative (2003) with the Southwest Climate Change Initiative (2006). It aims to reduce regional GHG emissions to 15% below 2005 levels by 2020, using a cap-and-trade system³⁵. However, six of the states that were initially involved preferred to act together under another agreement: the “North America 2050: A Partnership for Progress” (NA2050)³⁶. After their withdrawal, in 2011 the WRCI was materialized in the “Western Climate Initiative”³⁷, a non-profit corporation that helps in the implementation of regional cap-and-trade schemes. In parallel, the NA2050 was launched in March 2012 and is open to all US states, Canadian provinces and Mexican states. This initiative does not entail emission markets, while pursuing efforts towards the creation of a low-carbon economy through the collaboration in 6 thematic working groups (benefits; power; industry; sequestration; sustainable biomass and offsets).

Nevertheless, California continued its tasks to implement a regional carbon market, thus keeping to the original WCI milestones in the «California Cap-and-Trade Program»³⁸, also known as Assembly Bill 32 (AB32): first period – 2012-2014 (compliance started in 2013); second compliance period – 2015-2017, including new fuels, namely from transports; and finally 2018-2020 the third and last period.

California is the state responsible for the largest share of the USA gross domestic product, 13% in 2012, corresponding to 2 trillion US\$. It is one of the largest economies in the world. Private services comprise 29% of its GDP in 2012. In fact, if we add other services sectors within the industry category we reach 62% across all services (excluding Government services)³⁹. California is also the top exporting state, highly dependent on both interstate trade and international exchanges. Main sales sectors include electronic products and agriculture goods.

On energy, California consumption of 7858.4 trillion BTU (2011) by end-use sectors is shared by residential (19%), commercial (20%), industrial (23%) and transportation (38%)⁴⁰, in line with the

³⁴ Western Regional Climate Action Initiative: <http://www.westernclimateinitiative.org/history>

³⁵ <http://www.westernclimateinitiative.org/designing-the-program>

³⁶ North America 2050 official page: <http://na2050.org>

³⁷ Western Climate Initiative, corporation: <http://www.wci-inc.org/>

³⁸ California Cap and Trade Program: <http://www.arb.ca.gov/cc/capandtrade/capandtrade.htm>

³⁹ All statistic economic data retrieved from US Department of Commerce, Bureau of Economic Analysis (BEA) at >Interactive Data > GDP from: <http://www.bea.gov/> on 7th January 2014.

⁴⁰ Energy data previous to 2012 retrieved from U.S. Energy Inf. Administration’s (EIA) > State Energy Data System (SEDS), <http://www.eia.gov/state/data.cfm?sid=CA#ConsumptionExpenditures>, 8th January 2014.

important role of the tertiary sector in this economy. Looking at the energy source of consumption, we find a 28% share for natural gas, hence the largest energy source in the state, followed by motor gasoline excl. ethanol (22%) and fuels (residual, distillate and other) (21%). In smaller shares we find 11% from net interstate flow of electricity, 7% from biomass and other renewables, and finally, 5% from nuclear electric power, 5% from hydroelectric power, 1% from liquid petroleum gas (LPG) and 1% from. Final electricity use totalizes 21%⁴⁰. California largely considers the need for rapid intervention capacity in these markets, consequence of the electricity supply crisis of 2000-2001 (Wolak 2003).

On the production of primary energy, California produced around 2624.5 trillion BTU, 2011. Having the largest oil fields in USA, crude oil and natural gas account for 43% and 11% of CA energy production. 15% from nuclear electric power and 32% for renewables complete the share. California's electricity system generates more than 200 000 GWh per year. The current shares of generation per energy source include approximately 63% natural gas, 9% hydroelectric, 18% other renewables, 9% nuclear and 1% coal⁴⁰. In fact, California produces 70% of the electricity it uses. The state imports the remaining amount from the Pacific Northwest (10%) and the U.S. Southwest (20%)⁴¹. Currently, electricity in California is provided by about 75 load-serving entities, including 6 large investor-owned utilities and 48 publicly-owned⁴².

California challenge on electricity under AB32 is to secure supply with 33% renewable sources, while reducing GHG emissions. In this context and for the purpose of this paper, it is important to acknowledge the primary energy mix for imported electricity. In Table 1 we present power generation per source and geographic origin, and it is worth noting the percentage increase in coal and natural gas fuels, when including imports. Also, the unspecified power sources account for 16.40% of total generation.

Having presented the economic and energy background of US state of California, the associated greenhouse gas emissions, mainly resulting from fossil fuel burning, come as no surprise⁴³: of a

⁴¹ Electricity data from 2012 retrieved from CA Energy Almanac, 8th January 2014, <http://energyalmanac.ca.gov/electricity/>

⁴² Load serving entities: Investor-Owned Utilities - 6; Publicly Owned Utilities - 48; Rural Electricity Cooperatives - 4; Native American Utilities - 3
Other Electricity Service Providers - 14. The five largest utilities and total electricity consumption (in 2007) are: Southern California Edison Company (SCE) - 88,208 MMkWh; Pacific Gas and Electric Company (PG&E) - 85,057 MMkWh; Los Angeles Department of Water and Power (LADWP) - 24,317 MMkWh; San Diego Gas & Electric (SDG&E) - 20,300 MMkWh; Sacramento Municipal Utility District (SMUD) - 10,917 MMkWh. Information in: <http://energyalmanac.ca.gov/electricity/utilities.html>.

⁴³ Methodologies used in the inventory are consistent with the 2006 IPCC guidelines, and use global warming potential (GWP) values from the IPCC Second Assessment Report.

total of 448 MMTCO₂eq. (million metric tonnes of CO₂ equivalent) emitted in 2011, 38% originates in transportation, 23% from industrial sources, 19% from electricity generation (10% imported plus 9% in state), 7% from residential, other 7% from agriculture and forestry and 5% from commercial sectors (data: California's Greenhouse Gas Inventory by Sector & Activity⁴⁴).

Fuel Type	In-State Generation	Imports NW	Imports SW	Total Power Supply	% In Total CA mix	% in In-State mix
Coal	1580	561	20545	22685	7,50%	0,80%
Large Hydro	23202	12	1698	24913	8,30%	11,70%
Natural Gas	121716	37	9242	130995	43,40%	61,10%
Nuclear	18491	-	8763	27254	9,00%	9,30%
Oil	90	-	-	90	0,00%	0,00%
Other	14	-	-	14	0,00%	0,00%
Renewables	34007	9484	3024	46515	15,40%	17,10%
Unspecified	N/A	29376	20124	49500	16,40%	N/A
Total	199101	39470	63396	301966	100%	100%

Table 1 : Power generation in California, per source and geographic origin

(Data source: CA Energy Almanac)

California's emission goal under AB32 is 427 MMTCO₂e in 2020, i.e. equalling 1990 estimated emissions. The strategy to achieve this reduction (and an 80% reduction in 2050 below 1990 levels), is presented in AB32. It includes the implementation of a cap-and-trade scheme that sets a limit on emitters that are globally responsible for 85% of total GHG emissions reported in the California inventory. Phase 1 of CA carbon market occurs between 2012 and 2014, including as participants, electric utilities (both producers and importers), and industrial facilities that emit more than 25MtCO₂ per year. From 2015 on, distributors of transportation fuel, of natural gas and other fuels are also included. The emission permit unit is the CCA or California Carbon Allowance. On initial allowances distribution, there is initially free allocation for electric utilities (not generators) and industrial facilities to benefit ratepayers, but which decreases over time.

⁴⁴ California's Greenhouse Gas Inventory official page: <http://www.arb.ca.gov/cc/inventory/data/data.htm>

There will also be quarterly auctions of CCAs with a minimum price of \$10 in 2012, rising 5% annually over inflation.

An “Allowance Price Containment Reserve” (APCR) is a strategic reserve of up to 7% of all emitted permits. These permits will be available for sale at auctions dates, priced at 40\$/45\$/50\$ in 2013, that will also increase by 5% per year above inflation (i.e. in real terms). Because these sales are set at pre-defined prices, a measure of knowledge and stability is provided to the market, reducing opportunities for carbon price peaks. The APCR acts thus as a price volatility control mechanism. Also, banking of CCAs is allowed, but not borrowing from future periods.

On the access to offset credits (credits generated by emission reduction projects that reduce emissions of GHG outside of California), they are allowed for compliance up to 8% of the emission limit, per emitter. They must originate in CARB approved protocols. To date, these include forestry, urban forestry, dairy digesters, and destruction of ozone-depleting substances projects⁴⁵. They are also initially limited to projects within the country. The use of Certified Emission Reductions (CERs) from the Kyoto Clean Development Mechanism, the world largest offset market, is not allowed for compliance. Finally, AB32 linked its system with that of Quebec, Canada, on January 2014.

California Carbon Allowances, or CCAs, are traded in the Intercontinental Futures Exchange US (The ICE Futures US)⁴⁶ a leading trade for commodity markets. Currently, traded products are CCAs Vintage Futures for 2013-2016, and corresponding options on futures. Only very recently the full time series for ICE CCA 2013 futures was made available by Climate Policy Initiative⁴⁷. For this reason there still isn't any research published on actual California carbon prices.

There are only two carbon markets quoted in stock exchanges that enable access to daily prices. The oldest one is the European Emission Trading Scheme (EU ETS). The latest emerging GHG market is in California, under the Assembly Bill 32 (AB32). Whereas there has been extensive research on carbon prices, built mainly on data from EU ETS, we present a first econometric analysis of the California carbon allowances prices, after they started to be traded in August

⁴⁵ CA Compliance Offset Program official page: <http://www.arb.ca.gov/cc/capandtrade/offsets/offsets.htm>

⁴⁶ CCA at The ICE: <https://www.theice.com/productguide/ProductSpec.shtml?specId=6747556#>

⁴⁷ Climate Policy Initiative official page: <http://climatepolicyinitiative.org/>

2011. The emerging greenhouse gas (GHG) market in California is an important instrument to meet the goal of reaching the state's 1990 emission levels by the end of this decade.

So far, studies on USA carbon markets have focused on design features, initially looking at national level, proposing the use of auctions for allowance allocation (Fischer *et al.* 1998) and later, modelling the Lieberman-Warner Bill (Peace and Juliani 2009). A topic that has received more attention has been the consideration of electricity imports when accounting GHG emissions, to prevent carbon leakage. Bushnell (2007), Bushnell and Chen (2012) and Bushnell *et al.* (2014) compare GHG accounting at load-serving level, «first-seller» approach and pure source-based system and considers that including imports has only marginal benefits in California market. The analyses of the power market performed by Hobbs *et al.* (2010) and Chen *et al.* (2011) also conclude that downstream regulation is not necessarily the most efficient. Finally, Thurber and Wolak (2013) simulate impacts of high-carbon-price conditions, thus also advocating permits auctions.

Other sectoral features on the California carbon market and climate policy have been studied by Sivaraman and Moore (2012), who look at the impact of CO₂ pricing on photovoltaic (PV) systems, and Fine *et al.* (2012), who study the result of avoided expenditures originated by gasoline and diesel fuel price spikes, due to the existence of a carbon market.

Further literature review on carbon prices research was previously noted in the introduction of chapter 3. Briefly, carbon price variations origins and effects have been studied mostly through Granger causality tests, in a one-direction analysis. GARCH models have more recently been used on carbon prices volatility analysis and some use vector autoregressive models (VAR) to estimate the impulse-response functions between several variables, namely, stock prices of clean energy firms, energy and carbon markets. Previous studies of European Union Allowances (EUA), the carbon license unit in the EU ETS, relate carbon prices with industrial production (Alberola *et al.* 2009a) and causality from electricity prices to CO₂ (Keppler and Mansanet-Bataller 2010), from natural gas to CO₂, and from CO₂ and gas prices to electricity prices (Mansanet-Bataller *et al.* 2007, Fezzi and Bunn 2009). More recently Aatola *et al.* (2013b) show strong relationship between German electricity prices and gas, and coal with the European carbon price in 2005-2010. Lutz *et al.* (2013) conclude that the most important EUA drivers are changes on the stock market and on energy prices. To our knowledge, there is no previous study of the Californian carbon market prices.

Our aim in section 3.3 is to describe what drives CCA prices in these early stages of the Californian carbon market, and the effects that these prices are already having. Looking at data from

CCA futures, and the AB32 accounting obligations, we relate it with variables affecting economic decision of emitters: primary and secondary energy prices and an economy activity index. In the VAR model we also include temperatures as the exogenous proxy for energy demand, in line with Keppler and Mansanet-Bataller (2010).

3.3.2 Selected data

Recalling the rationale presented in the similar section for the EU analysis, the main purpose of an emission's market is to reduce emissions at the lowest overall cost, by assigning property rights where they previously did not exist. So, to allocate a limited number of emission permits, and allowing the exchange at a price, rational agents will allocate reductions to the most cost-effective solutions. An emitting facility will plan its emissions considering costs (e.g carbon price), the selling price of its good and expected trading quantities. So, carbon prices, energy prices, weather and the economic activity are variables that should be interconnected.

An important difference between CA market and EU ETS regards the inclusion of crude petroleum and natural gas extraction sector that does not exist in Europe. All other CA trading sectors⁴⁸ are, in their essence, energy intensive and/or high emission sectors, such as the EU sectors. Also, electricity imports are considered in CA trading through its primary energy source mix. Considering these AB32 market fundamentals and other previous work on European CO₂ prices causality (Alberola *et al.* 2009a, Fezzi and Bunn 2009, Keppler and Mansanet-Bataller 2010, Sijm *et al.* 2012, Aatola *et al.* 2013b, Lutz *et al.* 2013, Nazifi 2013) our model considers seven variables: CO₂ price (CCA), electricity, gas, coal, oil and gasoline prices, average state temperature and an economic activity index — Dow Jones Utility Index, DJU. Given a previous analysis of prices in California that showed no significant results regarding coal, gasoline and the economy performance, the wavelet analysis only considers the relation between carbon, electricity, oil and gas.

⁴⁸ Sectors included in AB32 carbon trading: Petroleum Refineries; Crude Petroleum and Natural Gas Extraction; Cement; Industrial Gas; Mineral Mining and Lime; Fruit and Vegetable Canning; Glass; Paper; Dairies; Iron, Steel, and Aluminium; Chemical, Biological, and Pharmaceutical; Breweries, Wineries, and Juice. In: <http://www.arb.ca.gov/cc/capandtrade/allowanceallocation/allowanceallocation.htm>

CO₂

The carbon market of California (AB32) started operations in 2012, with emissions compliance from 2013. Currently AB32 has 3 planned phases to reduce emissions: 2012-2014, 2015-2017 and 2018-2020. The unit of this market quoted on the stock exchange is the California Carbon Allowances Vintage Futures and options on these futures, for 2013, 2014, 2015 and 2016. The products are available at The ICE⁴⁶, and their daily rate is published weekly. In this study, we used the available daily series on the CCA Future Vintage 2013 released by Climate Policy Initiative S. Francisco of The ICE data. Data was available from 29/08/2011, and 563 observations were included, without missing information. Average value was of 15,05 US\$ per CCA, reaching a maximum level of 23,75 US\$ and a minimum of 11,55 US\$ per CCA, visible in Figure 20:

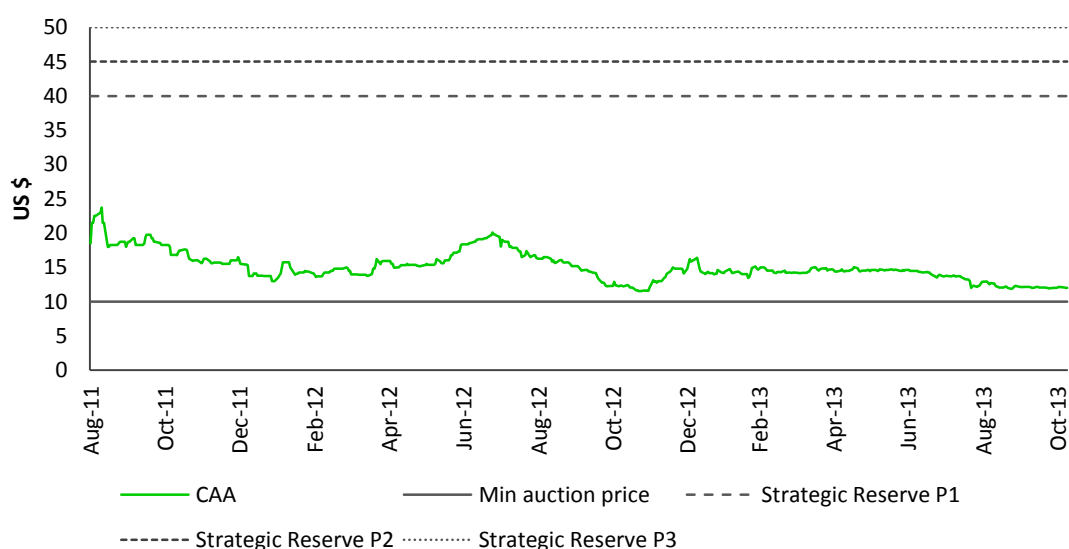


Figure 20: California carbon prices, 2011/2013

(Data source: The ICE⁴⁶, retrieved from CPI, California Carbon Dashboard⁴⁹)

We represent the emission prices (CCAs), in Figure 20. The limits on US\$ axis are intentionally 10 - 40 US\$, for these are the expected CCA price thresholds. 10US \$ is the minimum CCA value at auctions and 40 US\$ is the minimum price from the strategic price containment reserve.

⁴⁹ California Carbon Dashboard: <http://calcarbondash.org/>

Energy

The AB32 program covers nearly 600 emitting facilities, responsible for 85% of CA emissions. Phase one includes electric utilities and large industrial facilities that emit more than 25 MtCO₂/year, and in phase two distributors of transportation, natural gas and other fuels will also be added. Therefore, in line with market fundamentals and mentioned authors, we expect energy markets to have an expected relation with carbon markets and energy prices were included in our model. We include in this category representative electricity prices, oil, natural gas and coal prices, and gasoline prices.

Regarding the electricity variable, we considered the wholesale day ahead price of SP15 EZ Generation Hub, located in California. Data source is The ICE exchange. It was retrieved from the US Energy Information Association (EIA) information page for ten major electricity trading hubs in USA⁵⁰. Prices are in US\$/MWh and were included from 29/08/2011 to 08/11/2013, with only 19 days of missing data.

Oil prices regard the West Texas Intermediate (WTI) Light Sweet Crude Oil Futures (one month future), exchanged and available at The ICE, at US\$ per US barrel (\$/USbbl). No missing data.

For natural gas prices we used Natural Gas Futures Contract 1 (Dollars per MillionBTU - MMBTU), or one month futures, available from the US Energy Information Association (EIA)⁵¹. The source is the New York Mercantile Exchange (NYMEX) and the prices are based on delivery at the Henry Hub in Louisiana. Minor missing data (9 days) for the time length considered, totalizing 555 observations.

As for coal, Powder River Basin Coal Futures, front month, were also collected from The ICE database. Quotation is in US\$/tonne of Coal. Again, there is almost no missing data (563 obs).

Gasoline prices are Los Angeles Reformulated RBOB Regular Gasoline spot prices, available from the US Energy Information Association⁵², in US\$/gallon. One month futures are only available for the New York Harbor area. We selected the LA prices because spot and futures prices have a correlation value of 0.80, and we consider the geographic reason important.

⁵⁰ EIA electricity data: <http://www.eia.gov/electricity/data/browser/>

⁵¹ EIA natural gas data: <http://tonto.eia.gov/dnav/ng/hist/rngc1d.htm>

⁵² EIA gasoline data: http://www.eia.gov/dnav/pet/pet_pri_spt_s1_d.htm

In Figure 21, we can see the evolution of previously referred energy prices. Like in the previous section, we did not consider variables as the Clean Dark and Spark Spreads, or the «carbon switch» because they are linear combinations of variables included.

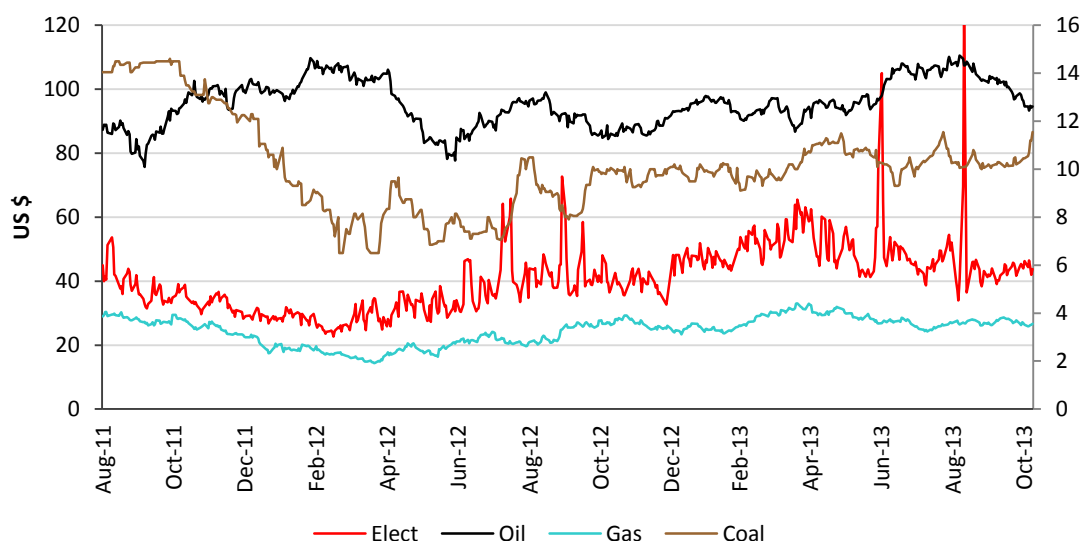


Figure 21 : California selected energy prices, 2011/2013

(On the left vertical axis we refer to electricity and oil prices. The right axis refers to gas and coal prices. Data sources: referred in text.)

Economic activity

Industries in California AB32 market are energy intensive and/or emission intensive, such as in the EU ETS. So, it is reasonable to expect a linkage between economic growth and their production levels. Following Chevallier (2009), Alberola and Chevallier (2009), Keppler and Mansanet-Bataller (2010), we included a stock exchange index as an economy performance proxy. For this study we chose the Dow Jones Utility Index⁵³ (DJU), a stock index that tracks the financial activity of 15 large US utility companies, available at YahooFinance. Daily price returns were included, with only 10 days missing since 29/08/2011. There is a total of 553 observations in this time series.

⁵³ DJU official description page: <http://www.djaverages.com/index.cfm?go=utility-overview>

Weather

Following Keppler and M. Mansanet-Bataller (2010) we included in this work daily California temperatures. Using RAWS USA Climate Archive⁵⁴ we gathered average values from eight representative weather stations (Kneeland, Lassen Lodge, Black Diamond, San Jose, La Panza, Oak Creek, Apple Valley). Daily average of this temperatures was then calculated from 29/08/2011, totalizing 563 observations, without missing information. As in the EU model, this variable is considered in the model as exogenous. For accountability of global warming effects, temperature would have to be endogenous. However, this aspect would only be relevant if we had data for several decades, which is not the case.

3.3.3 VAR analysis

To estimate the dynamics amongst various variables, we will rely on a VAR model and on a set of impulse-response functions and Granger causality tests. We have seven endogenous variables and one exogenous variable, the average temperatures. The seven endogenous variables include representative prices of CO₂, electricity, gas, coal, oil, gasoline and an economy stock index. To account for non-stationarity issues, all variables were transformed to first differences of log data. Stationarity of these time series was established by typical tests. We rely on likelihood ratio test statistic to decide on the number of significant lags to include in the VAR model. The test points towards the consideration of 18 days/lags, corresponding roughly to one month of daily data.

3.3.3.1 Causality and feed-back relations

The endogeneity or exogeneity of variables is a central question in VAR models, as discussed in section 2.1. As in the EU ETS case, temperature was the only variable considered exogenous *a priori*. For all other variables, we ran Granger causality/block exogeneity tests to perceive if any variable should be treated as exogenous. In these tests, a χ^2 Wald statistics is given for each

⁵⁴ Remote Automated Weather Stations (RAWS) USA Climate Archive official page: <http://www.raws.dri.edu/>

equation for the joint significance of each other lagged endogenous variables in the equation, as well as a statistic for joint significance. The results are described in Figure 22:

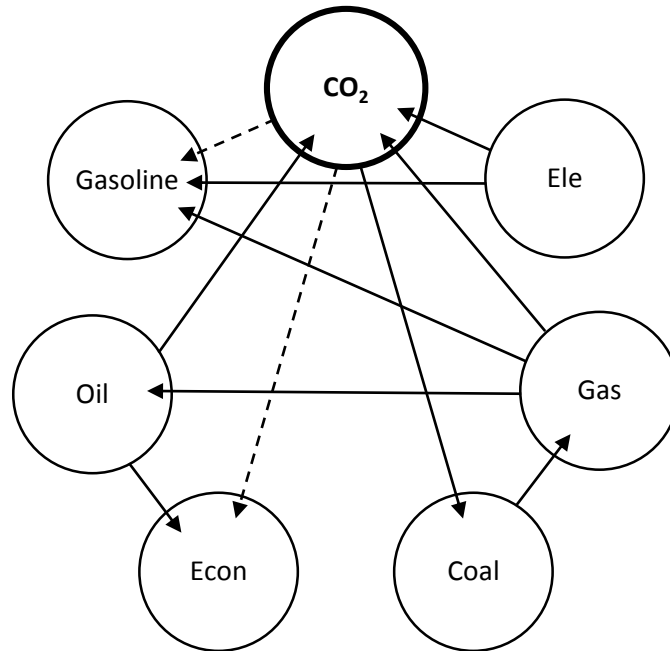


Figure 22 : California prices - Granger causality tests

Data: 29/08/2011 – 08/11/2013. Dashed/continuous arrows indicate causality at 10%/5% significance.

Regarding CO₂ price returns, we find significant causality from oil, gas and electricity. These are expected results in line with finding from other authors (Alberola *et al.* 2008, Creti *et al.* 2012, Aatola *et al.* 2013b, Lutz *et al.* 2013), even though these are all studies based on European data. However, these studies often find other and differing significant causality relations towards CO₂ that are not visible in our work.

In a reverse view, we find a significant impact of CO₂ price returns in coal, gasoline and economic activity. The observed influence in coal is in line with the previous section regarding European data. This is possibly due to the inclusion in the AB32 market of emissions from imported electricity, its energy mix (Table 1), and the high emission intensity levels (1001gCO₂/kWh⁵⁵) of electricity generation with coal. The other energy variable where we find CO₂ influence is on

⁵⁵ Moomaw, W. et al, 2011, "Annex II: Methodology. In IPCC: Special Report on Renewable Energy Sources and Climate Change Mitigation" (ref. page 10), http://srren.ipcc-wg3.de/report/IPCC_SRREN_Annex_II.pdf , retrieved 18/03/2013

gasoline price returns. In fact oil refining and fuel transportation are activities already included in the market, so it is an expected result. Finally, our study somewhat surprisingly finds a causality relation from CO₂ to the economic activity, presented as the stock index for large utility companies. This is an interesting result that falls out of this paper scope, and should be left for further studies.

3.3.3.2 Impulse-response analyses

Our most interesting results come from the impulse-response analysis. Our model requires the pre-definition of an order in which the variables affect each other contemporaneously. After this initial moment, the model runs without further assumptions. Our Cholesky order of influence takes into account the VAR Granger causality tests, the AB32 carbon market fundamentals and the current economic situation. In this model with seven endogenous variables, we propose that, in moment zero, oil is only impacted by its own innovation, then coal is influenced by oil's innovation and its own, then natural gas, electricity, the economic activity and gasoline, follow the same logic, by the denoted order. Lastly, we consider carbon licences to be impacted by all innovations.

Variance decomposition

As referred in section 2.1.2.2, the Cholesky order is also needed when calculating the variance decomposition. We recall that this is auxiliary evidence of how much each variable contributes to each other in the model. As in the EU case, we present below, in Figure 23, the variance decomposition of carbon and electricity (others are available in the appendix section B.3).

It is visible in Figure 23, graph a), regarding CO₂ variance decomposition, that over time all other variables gain an almost similar importance. On electricity (b), around periods 5 to 10, we see an increase in the proportion of the economy and gasoline roles, over the electricity itself. Oil, carbon and other variables also gain a role in the electricity variance.

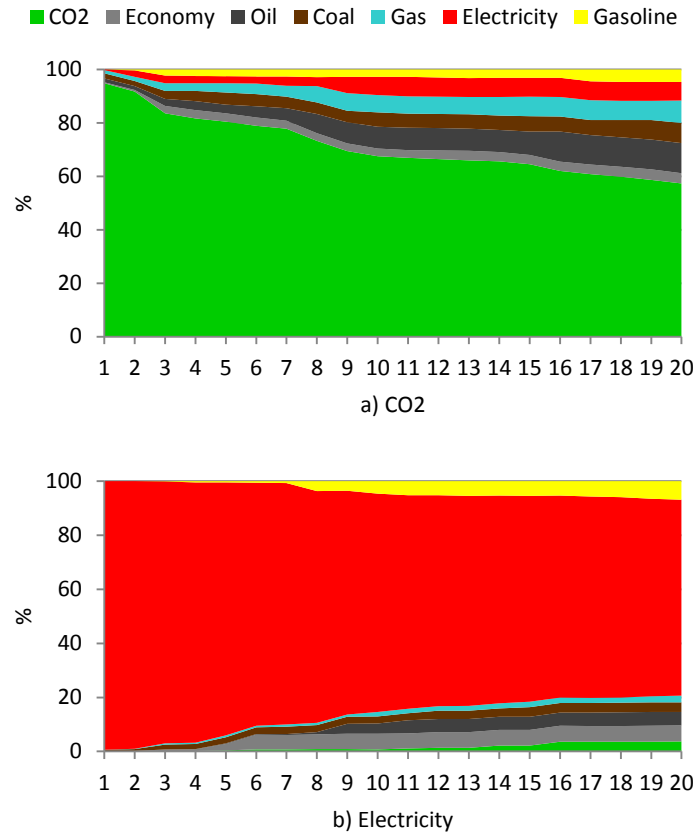


Figure 23 : Variance decomposition of carbon and electricity prices - CA

However, our main purpose is to look to the effects in carbon prices, when having a shock in other variables, or, to the effects in other prices, when having a shock in carbon. These can be seen through impulse-response functions.

Overall, we obtain 49 Impulse-Response Functions (IRFs). It is neither relevant nor prudent to analyse them all, because all our choices, such as the Cholesky ordering, were contingent on our interest in CO₂. Therefore, we focus on the IRFs associated with this variable.

First we look at the impact that an innovation in primary and secondary energy prices and economy performance has in CCAs. This would provide us information on the origin of California carbon prices. Secondly, recalling a carbon market goal of pricing emissions, we analyse the result of a CCA innovation in energy prices. Recalling that variables are in first log differences, we provide accumulated responses in the impulse-response functions for easier interpretation.

CO₂ response functions

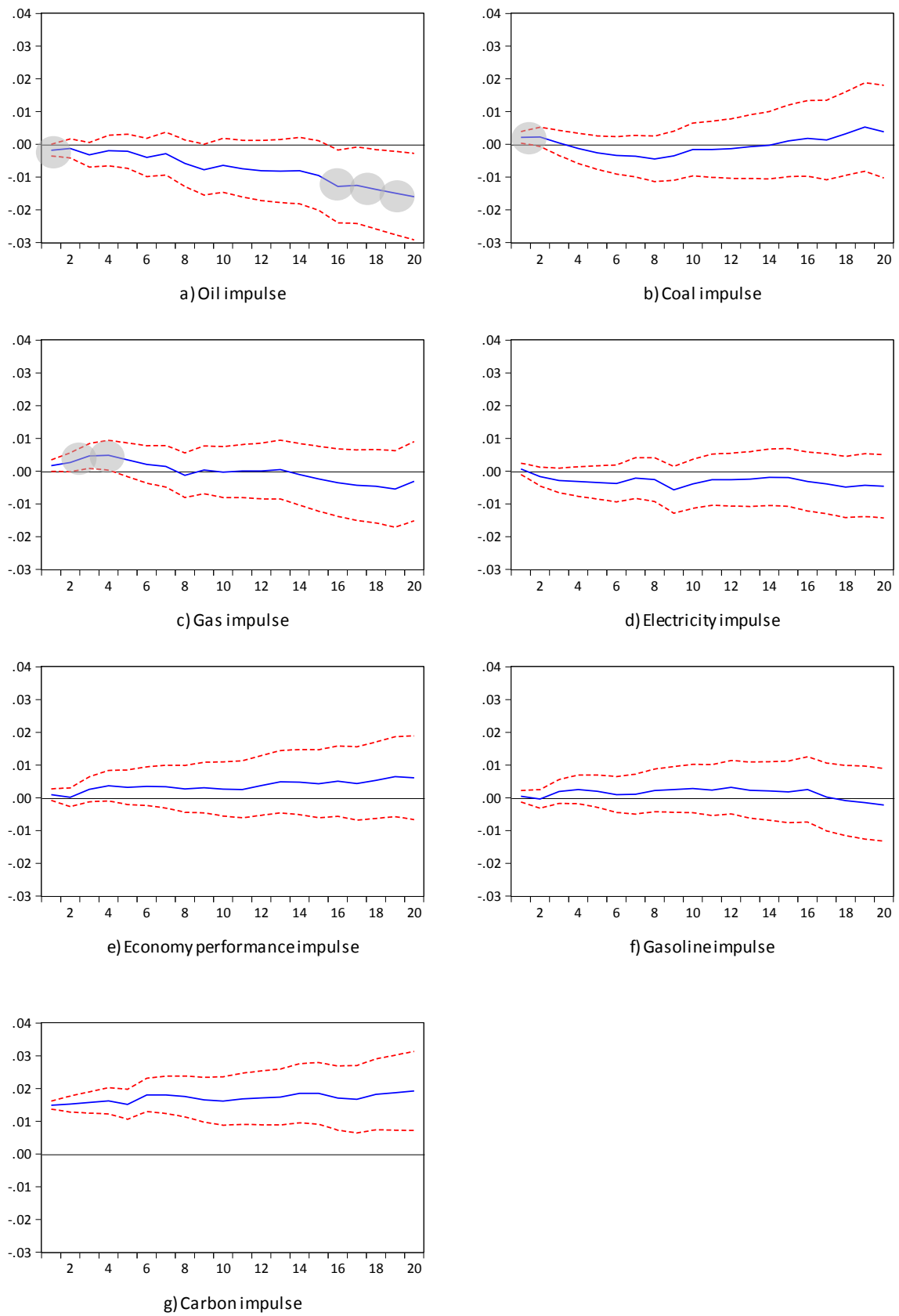


Figure 24 : CO₂ price returns accumulated responses to impulses in other variables - CA

(Blue line is the IRF; red dashed lines the limits of the 95% confidence interval. Grey circles indicate significance, whenever the function has both significative and non-significative values.)

Figure 24 represents the accumulated response of CO₂ to one standard deviation innovations in each variable. The last graph (g) in Figure 24 shows the response of a CO₂ impulse to itself. In the first three graphs (a,b,c) we see the impact in CO₂ of innovations in primary energy variables. All of them have periods of significative influence. Looking at natural gas we find a positive significative impact in the 3rd and 4th day after the innovation. In the next days we don't find significant results. It is a result that also occurs in Europe (Fezzi and Bunn 2009), and consistent with emission market notion that when gas prices increase there is an incentive to produce electricity with other fossil fuel, namely coal, that is more emission intensive, thus requiring more emission allowances for the same quantity of electricity produced. This is the idea behind the concepts of dark and spark spreads that decision makers consider when choosing the energy generation mix⁵⁶. However, coal impulse response function does not follow this rationale. In this graph, only in the first period, we see a marginally significant response of CO₂ to an impulse in coal. Although very small, the response is surprisingly positive, meaning that a positive impulse in coal prices has a CO₂ response of the same signal. This is possibly related to the indirect connection indicated in Figure 22 where the coal impact reaches carbon prices via an indirect path, through gas prices, suggesting that, in the first instant, a rise in carbon prices would increase demand for natural gas, thus following the same reasoning mentioned before.

It is worthy of notice that an impulse from the electricity price (d) has no significative result in CO₂ in any period, contradicting the Granger causality results presented earlier. This means that the causal mechanism identified earlier is not related to innovations in the electricity price, suggesting that electricity prices are relevant as a propagation mechanism of innovations on other variables.

In short, when looking at coal (b), gas (c) and electricity (f), in California, we are analysing the power market. It is possible to say that mostly primary energies influence carbon prices, while electricity may have an indirect impact. The result that coal, gas and electricity influence carbon prices is very well stated in previous research about European markets (Alberola *et al.* 2008, Fezzi and Bunn 2009, Keppler and Mansanet-Bataller 2010, Mansanet-Bataller *et al.* 2011,

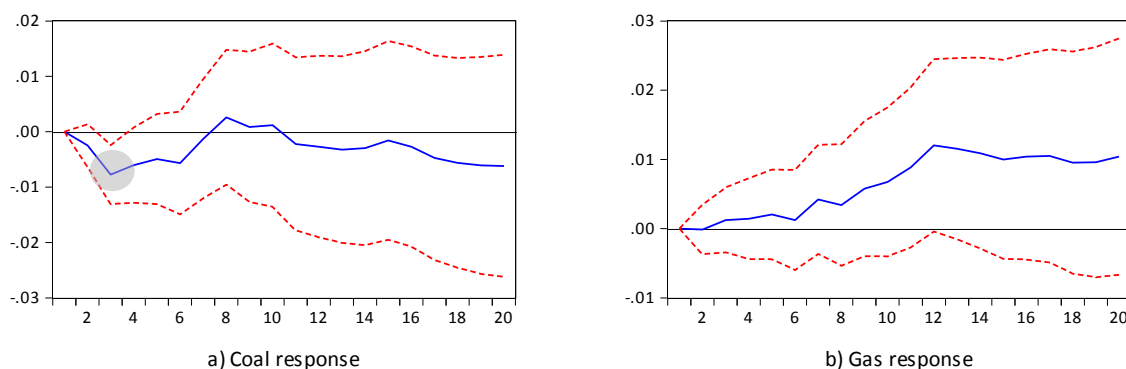
⁵⁶ Clean dark and spark spreads display the cost-efficient option for electricity generation in one period, either using coal or gas power plants, considering electricity, carbon, coal and gas prices.

Aatola *et al.* 2013b, a, García-Martos *et al.* 2013, Lutz *et al.* 2013). We validate the same idea for the Californian market.

Looking at oil (a) and gasoline (f) variables, more related to the transport sector, we find no significant response of CO₂ prices to an impulse in gasoline, in any period. This is an expected result given that the transport sector will only be included in the emissions market in January 2015. It should be interesting to re-analyse this feature with future data. However, we suggest that the importance of the future integration of the transport sector in the carbon market may be seen via oil prices. In the oil-carbon IRF we note a significative negative response after the 16th period that does not fade over time. This result reinforces the idea that when there is a rise in the price of energies with high emission levels associated, carbon prices will decrease because emissions are automatically being reduced. Also, the oil price impact will withstand in future periods, contrasting to gas and coal impacts that disappear.

CO₂ impulses

In Figure 25 we show the functions that represent the response of the several variables to innovations in carbon prices. The only IRF with significant results is the one associated with coal prices. The coal price reaction is coherent with the result in the causality analysis (Figure 22), and with other European causality studies (Keppler and Mansanet-Bataller 2010). The result is consistent with market fundamentals: when emission price increases, then emission intensive fuel, such as coal, is less demanded, so its price will decrease. This is a plausible justification essentially because AB32 includes imported electricity emissions, which is the main origin of coal use. So, it is likely that CCAs are, in some small level, in a day near the impulse, negatively influencing coal prices, considering at the same time the impact of all other variables in all periods. However, the response becomes insignificant after the 3rd day.



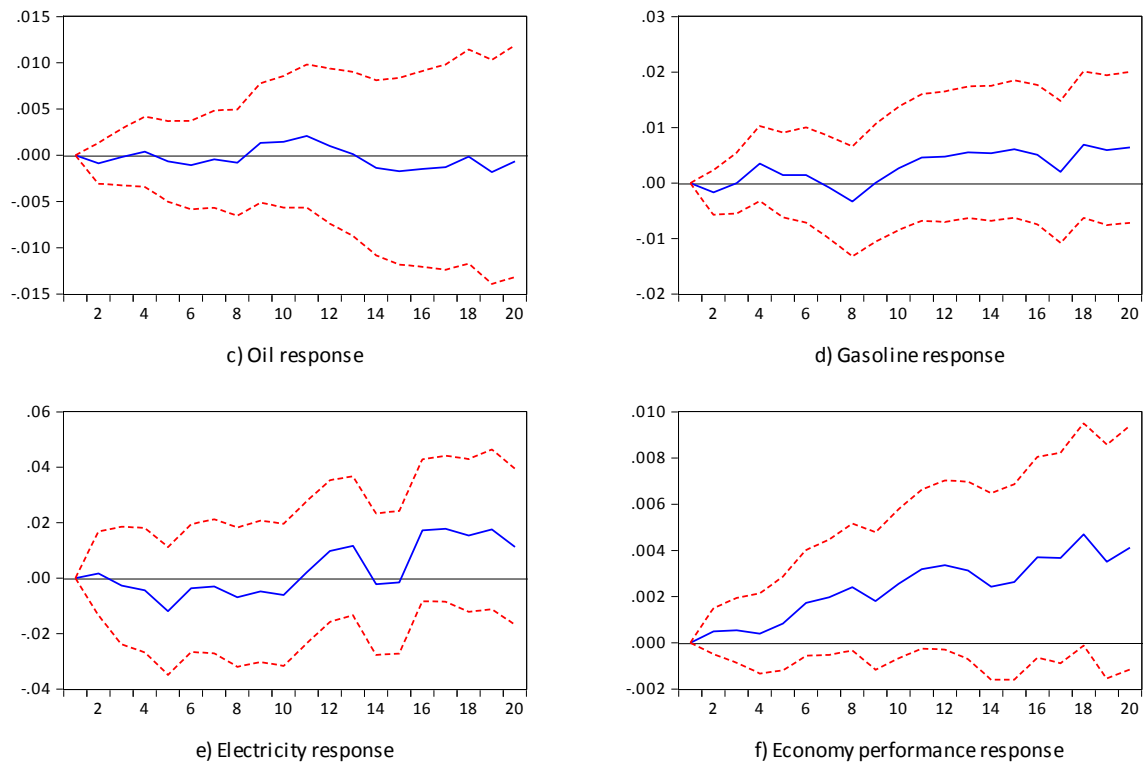
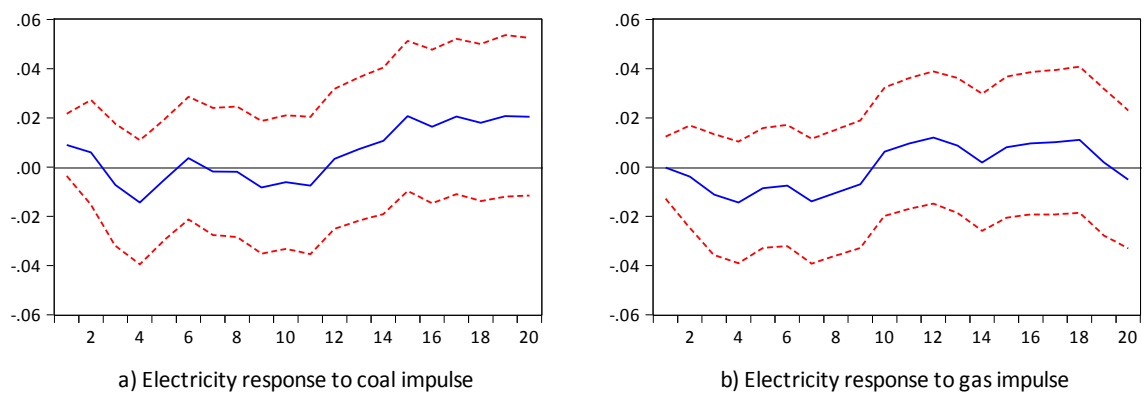


Figure 25 : Impulses in CO2 prices and accumulated responses of CA prices.

(Blue line is the IRF; red dashed lines the limits of the 95% confidence interval. Grey circles indicate significance, whenever the function has both significant and non-significant values.)

Other impulse-response functions, cycles and feedback

The following figures provide us with additional evidence on transmission mechanisms of information between different prices. Namely, between primary and final energies, previously identified as relevant.



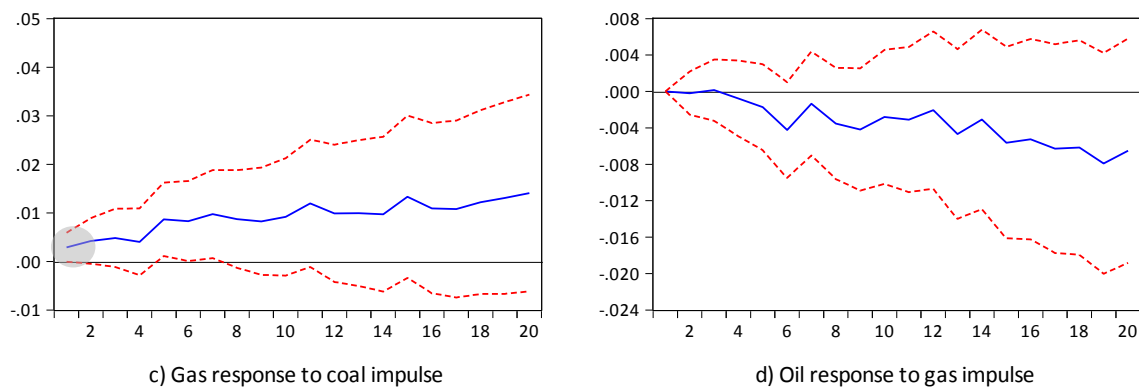


Figure 26 : Other accumulated impulse-response functions of energy prices - CA

The only significant evidence appears to be the response of gas prices to a coal impulse.

This is visible on the single cyclical relationship we find in the Granger analysis of the AB32 market, presented in Figure 27:

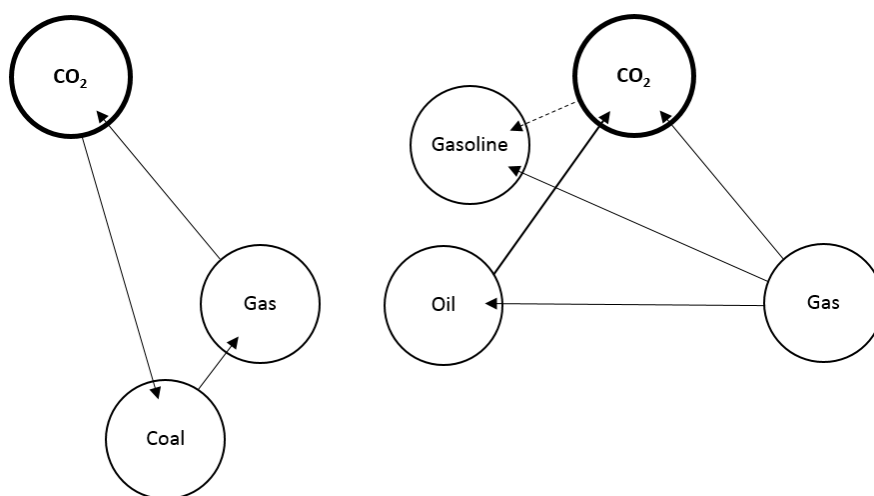


Figure 27 : Other causality relations of CO₂ - CA

Other interesting relation is the role of gas prices in this market. Its effect is rather scattered over other variables. This dubious relation is once again noted in the long-cycle analysis, in the following section.

3.3.4 Wavelets analysis

In this section we characterize CO₂ prices interrelation with energy prices in California. We work in the time-frequency domain, estimating how carbon prices behave at different frequencies and how it evolves over time.

We follow the previously referred studies and consider CO₂ prices interrelation with energy prices (in our case, gas, oil and electricity). We also included an economic activity index, but ended up excluding it because of statistically insignificant results. These are the critical variables for carbon market factors. In section 3.1 we already argued that multivariate wavelet analysis is particularly well suited for type of study.

The several variables are depicted in Figure 28, on the left-hand side panel, together with their wavelet power spectrum, on the right-hand side. The wavelet power indicates, for each moment of time the intensity of the variance of the time-series for each frequency of cyclical oscillations. This provides a first assessment of the behaviour of each variable in the time-frequency domain. It is interesting to note that the electricity prices are much less volatile than the other prices, with the blue colour dominating the most of the picture.

In the case of carbon prices, most of the volatility is observed before early 2013, and it is especially strong in the second half of 2012, period in which the wavelet power spectrum is statistically significant simultaneously at several frequencies. It is also worth referring that there is a statistically significant cycle, with period of about 12 months that runs from the beginning of the sample until the first quarter of 2013. Additionally, the periods of high volatility do not coincide. While markets for gas, electricity, coal and FTSE exhibit high levels of volatility until 2010, especially at 4 months frequencies (and also at longer run cycles, such as cycles with a periodicity of 20 months). Volatility in the CO₂ market is only apparent after 2012 and, especially, during 2013, at very high frequencies. Based on the wavelet power spectra it is difficult to discern any inter-relations between these markets.

The case of the other energy prices, gas and oil, is interesting. There are several regions of warm colours, both at several frequencies and several periods, but these are rarely statistically significant. In the case of Gas, the main significant region happens at high frequencies and slightly before mid-2012. In the case of Oil, the statistically significant region occurs for most of 2012 (and runs until early 2013) and is concentrated in the frequencies that correspond to cycles of periods of about 4 to 6 months.

Based on this preliminary analysis, it is difficult to guess how these variables relate.

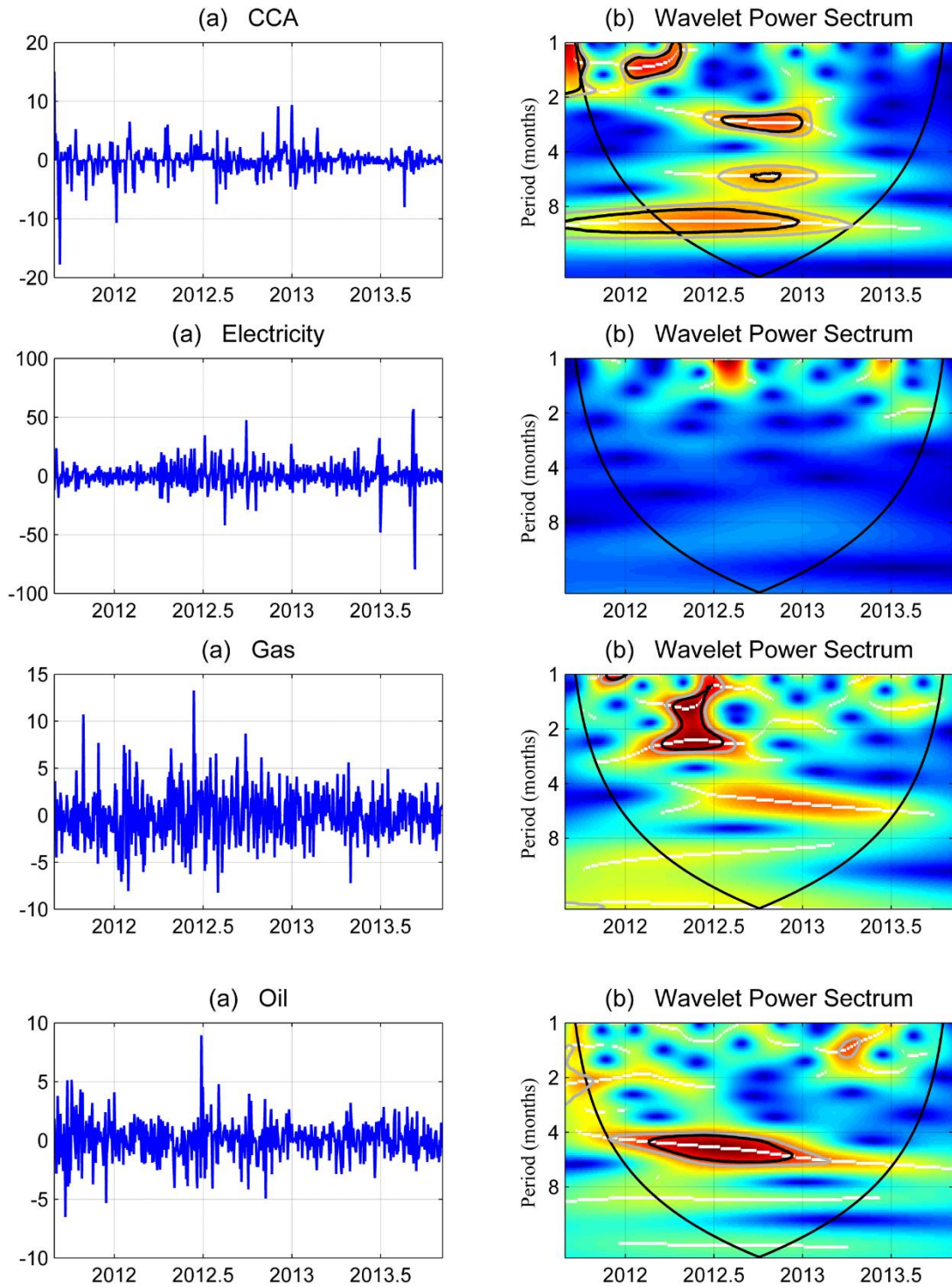


Figure 28 : CA prices - time-series plot and time-series wavelet power spectrum

(The black/grey contour designates the 5%/10% significance level. The cone of influence, which indicates the region affected by edge effects, is shown with a black line. The color code for power ranges from blue (low power) to red (high power). The white lines show the maxima of the undulations of the wavelet power spectrum.)

In Figure 29, we have the wavelet coherence between CO₂ and each of the other variables. Several conclusions can be drawn from these results. First, and perhaps surprisingly after Figure 28, there are large regions of high coherence. Between Carbon and Electricity prices, coherence, at low frequencies, corresponding to about one-year period cycles, coherence is statistically significant across the entire sample. For these frequencies, the phase-difference is essentially zero, showing that the two variables co-move together.

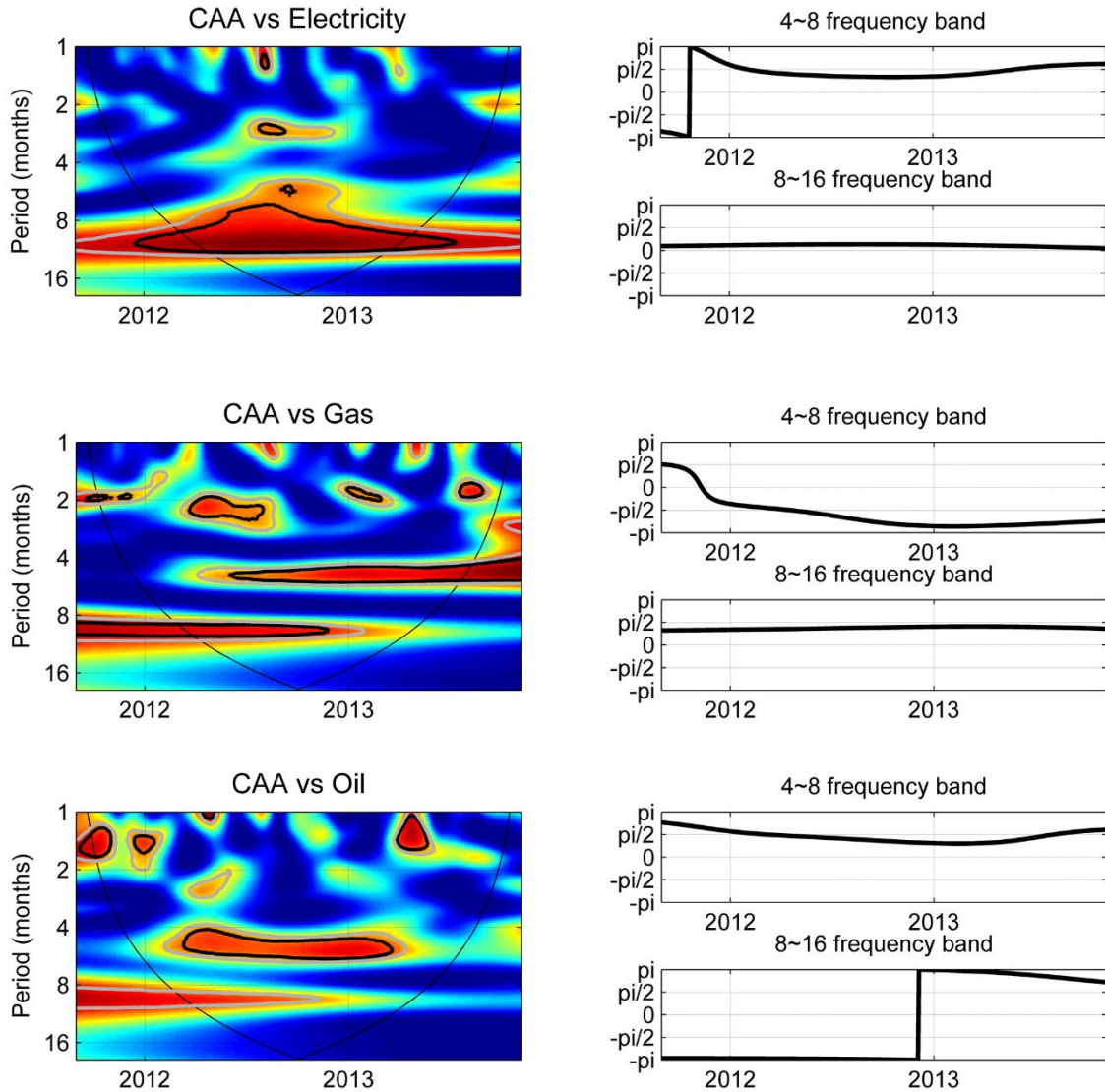


Figure 29 : CA prices - wavelet coherence and phase-differences

(On the left we find the wavelet coherence. The thick/thin black contour designates the 5%/10% significance level. The color code for coherence ranges from blue (low coherence --- close to zero) to red (high coherence --- close to one). On the right we represent the phase-differences between CO₂ and another variable (top: 2~8 frequency band, bottom : 8~20 frequency band)).

Between carbon and Gas prices the relation is not stable across time and frequencies. Until 2013, for frequencies corresponding to cycles of period eight or more months, coherence is statistically significant and the phase-difference, consistently between 0 and $\pi/2$, suggests that the variables are in-phase with the Carbon prices leading. However, the picture changes somewhat when we look at higher frequencies, corresponding to period of 4 to 6 month cycles. For these frequencies, coherence is statistically significant from mid-2012 onwards. The phase difference is consistently between $-\pi$ and $-\pi/2$, suggesting that variables are out-of-phase with carbon still leading.

The pattern for the relation between Oil and Carbon is not homogenous either. Again, we observe a statistically significant region until late 2012 for low frequencies, with the phase-difference being very close to $-\pi$, suggesting an almost perfect out-of-phase relation -- at most with a slight lead for Carbon prices. However, at higher frequencies, between 4 and 6 month period cycles, and running from early 2012 to early 2013, coherence is also statistically significant and the phase-difference is between 0 and $\pi/2$ telling us that the variables are in-phase with carbon prices leading.

Finally, in Figure 30, we have the wavelet partial coherence between CO₂ and each variable, after controlling for the other variables. The results are now much cleaner. In the first half of the sample, the regions of high coherence are situated at 8 months frequencies for gas and oil, slightly stronger in this case. The phase-difference is consistently between $\pi/2$ and π for such frequencies showing that the variables are out-of-phase, with gas and oil leading.

There is a rather small significant area in 4~8 months' frequencies where gas and CO₂ are out-of-phase with CO₂ leading, although this result should be considered with caution because of its size and location near the COI.

Coherence between CO₂ and electricity is stronger for frequencies above eight months after 2013. The phase-difference between 0 and $\pi/2$ suggests that variables are in-phase, with Carbon prices leading.

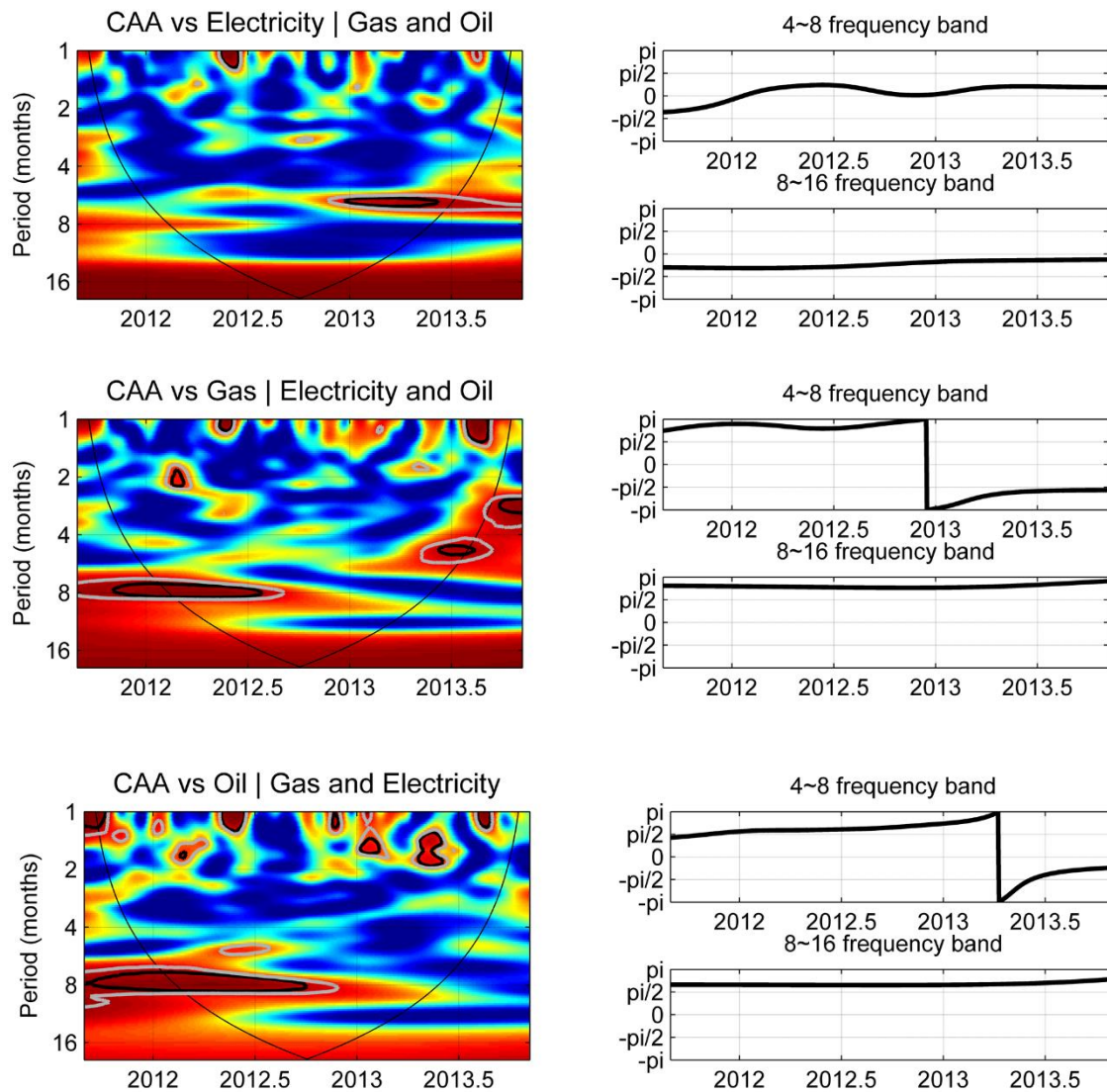


Figure 30 : CA prices - partial wavelet coherence and partial phase-differences

(On the left we find partial wavelet coherence. The thick/thin black contour designates the 5%/10% significance level. The color code for coherence ranges from blue (low coherence --- close to zero) to red (high coherence --- close to one). On the right the partial phase-differences between CO₂ and the other variable are represented (Top: 2~8 frequency band. Bottom: 8~20 frequency band))

3.3.5 AB32 synthesis of results

In the USA there is a history of regional and sectoral emissions trading schemes, in theory and practice, even though the country did not ratify the Kyoto Protocol. The latest emerging GHG market is in California, where, under the Assembly Bill 32 (AB32), the State signed a goal of reaching 427 MMTCO₂e in 2020, equalling 1990 estimated emissions. The proposed sustainability measures include the implementation of a carbon market.

In this section we present a first analysis of the carbon prices in AB32, the emerging California emission market. After describing the market main features, we study the interaction between carbon prices, energy prices including oil, gas, coal and electricity, and finally an economy performance index. We also considered average temperatures in California as the only exogenous variable that acts as a proxy for changes in energy demand.

In our VAR model, we first analysed Granger causality. Here, we find significant relations from oil, gas and electricity to CO₂ price returns. In a reverse view, we find a significant connection of CO₂ price returns in coal, gasoline and economic activity. In the IRF and MWA studies the results are similar, with the exception of electricity and the economy.

On CO₂ price formation we have natural gas, coal and oil significative impact of innovations. Our data suggests that mostly primary energies influence carbon prices, while electricity may have an indirect impact. In short, natural gas price has a positive result, showing an incentive to produce electricity with the more emitting thermal fuel alternative, which is coal. However, coal impulse does not follow this rationale, and even though the results are only very marginally significant, and in only one period, the response is surprisingly positive. On the variables more related to the transport sector, we find a negative response of carbon to an oil innovation, after 3 weeks, which does not fade over time. The oil result of the Granger causality and IRF analysis is consistent with the wavelet analysis, that shows an out-of-phase, oil leading, result. However, gas shows also an out-of-phase relation, leading until half of the sample, and following at two irregular intervals in the last year. In fact, the gas-CO₂ result is rather inconsistent. We consider the possibility of this long term relation being of spurious nature.

Regarding the impact of a carbon innovation, we find 5% significant results in the CO₂-coal relation, in the daily IRF analysis, and in CO₂-electricity analysis at eight month frequency. Coal is the fuel with highest emission intensity level for producing electricity, and electricity is 20% of California total emissions. Other industries already included in the market may not have had the flexibility to fuel-switch, and transports, corresponding to 38% of emissions will only be included in the market next year. However, AB32 includes imported electricity emissions, which is the main use of coal. Thus, it hardly comes as a surprise the possibility that CCAs are, in some small level, in a day near the impulse, negatively influencing coal prices, considering at the same time the impact of all other variables in all periods. Also, extreme cold weather was noted during 2013, requiring more power generation using coal, due to the insufficiency of gas. In the long term the direction of the result is similar to EU ETS, with electricity showing an in-phase relation with CO₂ with CO₂ leading, in the first half of the sample, at around eight months' frequency.

In future research, we should consider other carbon assets such as licences for future periods, not yet available, as well as other variables related to the transport sector, to be included in 2015. This is an important feature of this market, different from the EU ETS, the largest carbon market presently active. Further policy implications of our results in the AB32 market are referred in the discussion in chapter 4.

4 DISCUSSION

Carbon markets have multiplied around the world in recent years, and are now one of the key policies to fight climate change. Because of this, research on prices of carbon financial assets grew interest as did the number of polluting facilities facing GHG emission caps.

The work developed in previous chapters answers to two research questions about what causes changes in the carbon prices, i.e., what are the origins of its variations, and, on the other hand, what effects these variations have. These questions are divided into six sub-questions concerning the role and effect of primary and final energies.

This research is of major relevance to polluters, regulators of the carbon market, and consumers of energy intensive goods. In a cap-and-trade system, prices are a signal that guide the polluting companies' investments towards the use of cleaner fuels and energy efficiency. With the development of the carbon markets and higher liquidity levels, the consideration of the carbon price on polluters' production decisions should increasingly be transmitted to their products prices.

In our analysis, we considered two carbon markets, for higher robustness of results: the European EU ETS, oldest and largest, and the Californian AB32, very recent but expected to become one of the largest. To our knowledge, this is the first study to analyse the AB32.

On selected data, the rationale for choosing which variables to include was similar for both markets and followed previous studies and market fundamentals. Given a pre-defined quantity cap, prices are what reflects the marginal cost of abatement in an emissions trading scheme. Exchanged quantities may give us a notion of market liquidity, but not of correlation, causality nor subsequent cost-pass-through information. So, to analyse the dynamics of carbon prices we included the return rates of carbon prices, gas, coal, electricity and of a stock market index. CDM offsets (licences from projects that reduce emissions outside the market) were only considered in the European study, since the only allowed projects in the Californian market do not have quoted prices in the stock market. On the other hand, the California study includes oil and gasoline prices, variables directly related to the transport sector, which the AB32 considers under the market emissions cap, unlike the EU ETS. Average daily temperatures are considered as exogenous variable, in both models, as a proxy for variations in power demand. They are only indirectly connected to our research questions, and given the dynamic nature of our analysis, it would not be justifiable to consider this variable in any other form. But since previous authors show temperatures as a variable with significant effects in carbon and energy prices, we

acknowledge its effects in the impulse-response analysis. Looking to other studies, the only variables not included in our research, because they are linear combinations of other variables, were the clean dark and spark spreads (CDS and CSS) and the switching price of carbon, indicators for power utilities of the benefit of using gas or coal in power generation.

Still regarding selected data, in particular electricity prices in the EU, it is worth noting that emissions' abatement in the power sector may refer to the replacement of lignite for hard coal, as it is expected to occur in Germany. However, more expensive abatement solutions may happen with the exchange of hard coal by gas, e.g. in Spain and the UK (Fezzi and Bunn 2009). Although the study of the impact of carbon in different energy mixes is interesting, as noted by Pinho and Madaleno (2011), our aim was to globally analyse the European carbon market. Our choice for the combined electricity price index "Phelix" between Austria and Germany conveys a larger sensitivity to changes in carbon prices, mostly because the EU carbon prices have been low. Also, the high level of correlation between the considered Phelix electricity price index and other electricity prices in Europe (ranging from 0,85 to 0,92), provided us with the right input regarding Europe's power prices relation to carbon.

We use daily prices, *spot* whenever possible, which García-Martos *et al.* (2013) regards enough for forecasting studies of 12, 24 or 36 months horizons. Also, in wavelet analysis, other frequencies are captured through daily prices. This follows the information that abatement cost curve for power utilities is uncertain throughout the year, reflecting the changing demand and the costs of switching primary fuel. Although only having to submit emission allowances once per year, stakeholders operate in the daily market, buying and selling carbon permits under their own expectation of what the annual balance will be.

On the methodology, the vector autoregression models built and the multivariate wavelet analysis are similar for Europe and California.

In the VAR models, by allowing each of the endogenous variables to be explained by its and all other variables' past values, we consider the possibility of feedback effects. From the VARs, we obtain Granger causality information that considers the simultaneous effects of all variables. Here, we observe that the variables should all be considered endogenous (Figure 9 and Figure 22), which indicates our modelling choice. We also obtain impulse response functions, which allow us to analyse what happens, for example, to energy prices when there is an innovation in the carbon price. In spite of relying on a VAR model, because the carbon markets are very recent,

we do not consider the hypothesis of the presence of a long-term trend. Hence, we discarded the VECM approach.

The multivariate wavelet analysis (MWA) is also applied to both EU and CA markets considered and is particularly well suited for this purpose. Energy price dynamics is nonstationary and so it is important to use methods that do not require stationarity. Moreover, there is evidence showing that several energy markets display consistent nonlinear dependencies. The MWA tools purpose is to analyse the correlation between the various prices at different frequencies. It goes beyond the study of daily cycles that the VAR allows. To change power supply quantities, on a large scale, is neither easy nor quick, so, it makes sense to consider the possibility of correlations in longer temporal cycles, *i.e.*, corresponding to lower frequencies. This information, not previously examined by any author, is retrieved by multivariate wavelets analysis, which also proposes causality indications that we compare with the VAR results.

Below, we present a joint review of all short and long cycles results, in both markets, EU ETS and AB32, regarding: a) the influence of energy prices and the economy on carbon prices, and b) *vice-versa*. After, we look at the feedback relations. Observations on offsets, only considered in the European market, are also briefly noted. We finalize the chapter with comments on stakeholders' interests and policy implications

The results

For clarity purposes, we start with a summary table (Table 2) where we pinpoint the statistically significant results by methodology. This table indicates the importance of the variables:

CO ₂	Electricity	Gas	Coal	Economy	AB32 only	AB32 only	EU ETS only
					Oil	Gasoline	CER
Cause in CO ₂ / Consequence of CO ₂							

EU ETS

● Granger causality

◆ Impulse-response

✕ Wavelets

AB32

○ Granger causality

◇ Impulse-response

✕ Wavelets

Table 2 : Outline of obtained significant results of variables relationships with carbon price

Although Table 2 is useful to point out relations with CO₂, it is obviously too simplified. It does not identify the directions of the relationships, indirect associations, nor the time cycle of correlations. So, we now articulate the obtained results, by variable, to better understand the answers to our research questions.

An initial analysis of the power spectrum of each variable shows that the features of energy and carbon markets are different between EU and CA. Volatilities in CA were significative in 2012, while, in the EU, they were more visible until 2011. In this background, considering both these markets in our analysis provides us with more robust results.

a) The origin of carbon prices variations

Here we look at the upper triangles of Table 2. **Electricity, gas, oil and the economy** outdo other variables in explaining the variations of CO₂.

These results are in line with Chevallier (2011d) regarding the direct and fading effect of the economy, but refute Keppler and Mansanet-Bataller (2010) that only find direct effects from electricity and coal. Although only referring to the EU ETS phase I, Fezzi and Bunn (2009) find immediate impact of gas prices, but not of electricity.

First, we note that, in EU ETS carbon price, we found higher volatility after 2012, which may relate to the political uncertainties over the third phase of the market, starting in 2013. In AB32 market, the volatility of carbon price returns is rather dispersed after 2012, the beginning of the market and not as evident as in the EU ETS.

In more detail, looking at **electricity** effects, we find Granger causality, for daily cycles, in both markets. The European result of the impulse-response function is consistent and proposes a positive impact of permanent effects. This is in line with the information that power generation emits a large part of CO₂e emissions. So, if the electricity price rises, the CO₂ price is expected to act accordingly. However, in California, an electricity shock does not have a significant response, opposing the Granger causality result.

The **economy** shows an important positive role towards the carbon price, at all levels (causality in short and long cycles, and impulse-response) in the European market. However, in daily cycles, the impact is of short duration, fading after the first periods. On eight to twenty months' cycles, after the start of phase III (2012), we find evidence suggesting the existence of a yearly association between these variables. This is possibly due to changes in the carbon market that make it more able to react to macroeconomic factors, including the ending of free allocation of

carbon allowances to the power sector. We also find indirect rebound effects on the economy (Figure 9 : EU prices - Granger causality tests), arguing Chevallier (2011d), though he is only referring to the carbon-economy connection. However, we agree that this relationship is robust to shocks in other variables (Hintermann 2010, Chevallier 2011d). No evidence is presented of any influence of the economy variable in California.

On primary fuels effects on CO₂ price, namely gas and oil, we see they are much more significant in the AB32 market.

Oil price analysis provides the most coherent results. It shows a direct Granger causality, negative and permanent at daily and longer cycles. It is an expected result, not yet analysed by previous authors. One could argue the importance of oil in the economy, and a correlation/causality inaccuracy, but in AB32 we see that the economy does not have a significant effect on carbon prices, while oil does. So they are most likely independent results. This result reinforces the idea that when there is a rise in the price of energies with high emission levels associated, carbon prices will decrease because emissions are automatically being reduced. Also, the oil price impact will withstand in future periods, contrasting to gas and coal impacts that disappear. This variable was not considered in the EU analysis because the distributors of transport and heating fuels are not included in the EU ETS.

On **gas** prices, the results are significative for daily cycles, in Europe and California. Although, in Europe, we do not find a direct causality connection, it may be observed through an indirect path via electricity prices (Figure 16), sustained by the respective IRF (Figure 13). As expected, in both EU and CA, the relation is positive but of very short duration, disappearing after the first periods. This is coherent with the idea that the marginal cost of emissions abatement is equal to the gas price, when referring to the management of the dispatch order in power utilities. However, we didn't find significant evidence of correlation in longer cycles, in the EU ETS, and the evidence found in AB32 is most possibly of a spurious nature.

Finally, we also look at **coal** prices, although they only present significative impact in carbon in the impulse analysis in CA, and in long-cycles analysis in EU. Furthermore, the response of CO₂ to a coal innovation in CA is surprisingly positive. The explanation that presents itself regards the indirect relationship via cycle identified in the Granger causality (Figure 15), an idea that we validate through an impulse-response function between coal and gas (Figure 13). In contrast, the EU wavelet analysis results showed a negative relation, at lower frequencies (cycles 8 ~ 20 months), in line with the energy and carbon market fundamental idea that when a very polluting

source has a price increase, the carbon price does not need to follow, and may even decrease, for emissions are already being controlled.

It can be said that European carbon prices mostly reflect electricity price variations and economic developments, and therefore only consider information on the price of final energy. While in California, prices of gas and oil are the most important. This difference may be explained by the lag between the ages of both markets, and by the inclusion of the transport sector, and electricity imports, per fuel, in CA carbon market.

b) Conversely, significant influences of CO₂ are less than desired.

Now we interpret the lower triangles of Table 2. Briefly, only **electricity, coal and CERs present evidence of the impact of variations in carbon price return rates**. The remaining relations arise only in the Granger causality relations, of the AB32 market, and are neither supported by significant impulse-response functions, nor by the analysis of longer cycles. Once more, the eight month cycle relation with gas is briefly visible in the AB32 market. However, as mentioned in the previous analysis, we support the idea that this relation is of spurious nature, because of its lack of consistency.

On **coal**, in Europe and California, there is evidence of Granger causality from carbon. This result, while statistically valid, is only supported by the respective impulse-response function in the AB32 market, where an innovation in the carbon price has significant response of the price of coal. In principle, the coal market is a global market driven by global developments (Keppler and Mansanet-Bataller 2010), an evidence reflected in the significant impact of stock market developments in coal prices, consistent with Keppler and Mansanet-Bataller (2010). This is also emphasised in Europe by the impact of gas prices, a coal 'substitute', in electricity generation. However, in the AB32 market, the coal result is not present in longer cycles' analysis. Our theory is that this may be due to the inclusion of electricity imports, by fuel origin, in the California carbon market. Half of the electricity used is GHG emitter, and of this half, almost one third comes from coal. So, it is possible to assess that the price of the final 7% of electricity used in California originating from coal is influenced by information on the variation of carbon prices, in the first days after a shock in CO₂.

We also found another indication of causality concerning impacts of changes in carbon prices on **electricity** prices. The result arises in EU when there is an innovation in carbon pricing, and in both EU and CA studies at lower frequencies, which captures relations in longer cycles. In EU

shorter cycles, it occurs indirectly via coal prices or developments in the economy, disappearing after the first days following the innovation. This outcome follows the current general opinion that carbon prices are too low to have an immediate impact. However, the results are significant at eight months' frequency in CA and eight to twenty months frequency in EU. This result refutes previous analysis made with EU ETS phase I data, where an immediate and permanent causation is found from carbon to electricity (Fezzi and Bunn 2009, Keppler and Mansanet-Bataller 2010, Pinho and Madaleno 2011). However, with phase II daily-cycle data, even if only for the first years, Keppler and Mansanet-Bataller (2010) fail to find this relation, supporting our result.

With our results, we may suggest that only on a yearly basis power producers and regulators are inputting information of carbon prices in electricity prices. This is new information not captured by previous authors, which contributes to better understand the timing of price effects in a carbon market.

Resuming the two most significant impacts of carbon prices, our work notes an explicit effect on electricity, but not so explicit on coal. It seems that power suppliers are passing on the emission cost of using coal in their generation mix to the consumers through the electricity price, which is consistent with a low price demand elasticity of this good.

Finally, and only in California, an indication of carbon influence arises in **gasoline** prices, and the **stock market** index, as Granger causality indications.

It is also important to note that results show us that there is no evidence that penalizing CO₂ emissions depleted **economic activity** in the time frame considered. In short, in EU, carbon prices are related with energy prices, and they follow the economy tendencies, as mentioned above. No significant information on the direction of effects was found in the CA market.

On **CERs**, we recall they regard offset emissions of projects developed under the Clean Development Mechanism (CDM) of the Kyoto Protocol. This mechanism aims to assist developing countries in their sustainable development journey by allowing Annex I countries (industrialized countries) to finance projects to reduce emissions in Annex II (developing) countries. For these projects, emissions credits (CERs) are generated. CERs are only recognized in the EU ETS, so they were not considered in the AB32 analysis.

The CERs price, independent of the European carbon market, is shown to be influenced by the carbon price, as our initial hypothesis poses. This is because the EU ETS recognizes CERs in the fulfilment of an installation cap, up to a maximum of 10%. It is a positive relation, which meets the definition of a substitute good. The reverse is not visible because the developing country party that receives CERs, whenever harbouring a mitigation project, does not necessarily sells it

to European companies. CERs were not considered in the MWA because of the recent downfall in the CDM market. Expected results of this variable would never be sufficiently important to justify the additional computation needed.

One evident indirect result of carbon markets is the strengthening of the **link between gas and electricity** prices (Fezzi and Bunn 2009), visible in the respective impulse-response functions. There is a clear indication, as it is supposed to happen, for power producers to exchange the use of coal by gas, at the margin, visible in the carbon price effects on primary energy.

With our results in mind, in a very wider approach, we may say that carbon should reflect the marginal cost of gas. In this line of thought, Fezzi and Bunn (2009) even recall the real possibility of gas inheriting the geopolitical risk characteristics of oil via carbon markets. However, one must not forget that the marginal abatement cost, in the end, is guided by supply and demand of abatement itself. This aspect is very closely related to the problems associated with over-allocation of licenses that happened in the EU ETS. The amount to which this overallocation is mitigating the carbon price effect is being analysed by proper institutions, such as the EC, and is a topic for future research.

Research answers

Given the critical role that the included variables have, not only on a sectoral perspective but also considering their essential role in the economy of any country, our multivariate analysis at different frequencies provides evidence that the dynamic cross-correlations between variables are significant, therefore, useful for forecasting in future research. This work led to important results, namely the discovery of new relationships between energy, carbon and the economy variables, synthesized in the following answers to our research questions:

On carbon price drivers

1. Do final energy prices impact carbon price?

Yes, in case of electricity. No significant results are found regarding gasoline. The electricity has, however, an undeniable positive impact on carbon, for daily prices, immediate and permanent in the European case. In this case, our hypothesis is supported.

2. Do primary energy prices impact carbon price?

Yes, but only oil has permanent effects, and influence in longer cycles. We also found evidence of the immediate and short-duration influence from gas and coal prices. This relation mostly occurs in California. The direction is the expected, from gas (positive) and oil (negative). However, the positive connection with coal comes by an indirect path via gas prices.

3. Finally, on the macroeconomic perspective, does the level of economic activity translates into the carbon market?

Yes, positively, in the early periods and also longer time cycles, in the European market. This result is less robust than expected, because it does not have permanent effects, and it is not significant in the AB32 study. However it makes sense to be especially significant in the analysis of longer cycles.

On carbon price effects

1. Does carbon price influences final energy prices, including electricity and gasoline?

Yes, there is a positive impact on electricity prices, in both markets for longer cycles (4~8 in AB32 and 8~10 in EU ETS). It is also visible in the EU ETS daily analysis, disappearing after the first days. As for gasoline, there is only an indication of causality in the California market, not sustained by any other analysis.

2. Does carbon prices influence primary energy prices, including natural gas, coal and oil?

Only in the case of coal. This is visible in the Granger causality analysis in both markets, and in the AB32 coal response. As expected, the relation is negative.

3. Does the permit price impact the offset price (CER) in the EU ETS?

Yes, in a positive direction. As these licenses are substitutes of the EU ETS allowances to comply with the emission target, up to a limit of 10%, and are not recognized in any other market, the positive relationship found from the EUA to CER proves our original hypothesis.

Comments on stakeholders' interests and policy implications

The study and results presented here have tangible utility for companies under emission limits, for financial traders involved in carbon markets, for carbon and energy regulators, and also for consumers of energy intensive goods.

On the one hand, we obtained information on responses to shocks in different prices, key data for financial decisions of polluting companies and brokers. Hedging strategies in energy and carbon markets, to offset the risk of any adverse price movements, should consider that the relationships between prices are not constant. Our results demonstrate the need to take into account temporal information and direction of different shocks as well as the correlation at different frequencies. Concisely, our evidences from the short cycle's analysis facilitate the portfolio risk management of energy and carbon financial market players.

On the other hand, carbon prices origins and effects are also needed information to study and analyse the market operation and efficiency. In this perspective, the results we obtain in MWA for lower frequencies are of particular relevance to market regulators, States and also emitting companies, because they provide a perception of the annual relationships between decision variables. In the following paragraphs, we briefly comment on policy implications of our results in the EU and CA markets, and propose recommendations for the improvement of both emissions trading schemes.

Recently, Europe proposed a new policy framework for climate and energy, for 2030, where a reform of the EU ETS is presented. It is the regulator reaction to low carbon price levels, consequence of an overallocation of permits. It includes the establishment of a market stability reserve and an automatic adjustment of the allowances available in each allocation auction. The proposal refers that, starting in 2021, 12% of the total allowances in year $x-2$, shall be placed in the reserve. With the results from this study we consider that the intended effects of the carbon market are present, even if only in longer cycles. Knowing this, we propose that the EU ETS market stability reserve percentage (currently 12%), should be reviewed yearly or, at least, every two years, to account for the effects observed of carbon price in the electricity price, of coal and carbon relation, and finally, of the economy in the carbon price. It should not have an effect in the overall economic level variations. Recalling that the reserve amount is calculated using the allowances' number from two years before, it is relevant to repeat this study closer to 2019, and observe if new results are consistent with the ones presented here. Shorter cycle measures applied to the carbon market, such as the cancellation of a limited number of privately owned auctions, shouldn't have a significant effect in energy prices. Only structural, long-term

measures, such as a retirement of a number of allowances or early revision of the linear reduction factor should matter.

Regarding the recent Californian market, by the end of the first year of compliance (2013), the main source of information on financial carbon markets indicates an average of 1.8 MM weekly traded licenses in 2013, reaching 2.5 by the end of the year (The ICE, 2014⁵⁷), which displays an increase in market liquidity. However, a simultaneous fall in prices since the start of the year indicates that the market is probably facing an allowances' surplus. Three other aspects may be contributing to this surplus: first, the banking rules of AB32, allowed for future periods, though subject to some limits; second, the growing renewable power production, and increase in rain, in the Spring, fuelling hydro power plants; and finally, more recently, fewer than expected emissions originating in Québec, recently linked to the California carbon market. These three reasons may cause the prices to remain near the bottom limit until 2020. The surplus problem has also been affecting the European market for almost eight years, and California tried to overcome it by defining, in advance, market mechanisms to control the prices. They include a price floor at auctions and a price containment reserve to 'slow down' peaks. Despite this potential problem, there has been a growth of sales of licenses for future years, conveying the idea that the AB32 market will continue to operate, with credibility.

However, a possible dissatisfaction in AB32 is expected after 2015, in the 2nd period, when consumers will be directly affected by greenhouse gas emissions limits in transport and home heating fuels (by the inclusion of their distributors in the carbon market). The causal link between CO₂ and gasoline is already apparent in our study, although not significant when we cause a shock in the price of carbon. We expect this relationship to intensify and gain significance when new phase data is included. Until now, the carbon market was only tangible to consumers in a 'positive' way, when residents and small merchants received their 'climate' credits in the electricity bills. These credits regard the devolutions of values of sold carbon allowances that were allocated for free in the beginning of the year, and that the power generators did not use. Rules of the market state that they should be sold and its value given to customers. This is in line with our results that the carbon price did not influence the price of electricity in California in the first year.

⁵⁷ Carbon market North America available at https://www.point-carbon.com/polopoly_fs/1.3478414!CMNA20131220.pdf

Free allocation is not currently planned for fuels distributors, though one could argue that the licenses not used by the power sector could be channelled to them. Our evidence shows causality in variations from carbon towards gasoline prices, as an expected outcome of the carbon market, in future periods. However, attending the possible situation of a licences surplus, free allocation is an approach that may escalate the problem. Another option is to recommend costumers to save their 'climate credits' to accommodate the expected increase in gasoline and heating fuel prices. In this case, it would be an indirect way of supporting an increase in fuel prices, and even in future electricity prices, if that is to be the case, without tampering with the climate goal.

Looking to our results, the first year of compliance of the AB32 market may revive emissions' trading as a favoured measure for climate change mitigation, under the doubts mainly brought by licenses' surplus issues in the EU ETS and now in the AB32 market. But even in the recent AB32 there were significant relations between variables, most in the right directions (namely from carbon to coal and to gasoline) and the case of electricity reflecting the situation of allowances surplus (from electricity to carbon).

One should note some main structural differences between the EU ETS and AB32 market that are advantageous in terms of market efficiency. In AB32, the inclusion of fuels distributors, the accounting of electricity imports per fuel, the existence of a price floor and ceiling, and the return to consumers of the selling value of free allocated licences that have not been used. In EU ETS, the no-banking of licenses rule between periods. The AB32 features mean that the carbon price contains more information on GHG emitting activities and, more importantly, allows consumers of energy-intensive goods to be more aware of the cost of emissions. These are aspects that each market should be aware of in the other.

To finalize, we note that the results obtained in this study allow further knowledge on carbon markets and enhance previous research in three perspectives:

- A complete analysis of the multiple direction relationships between energy prices and carbon, considering effects of the economy and temperature;
- The study of effects on different frequencies that a single multivariate analysis does not show, using an innovative application of wavelets simultaneously to carbon and energy markets;
- More consistent information about carbon markets, by including phase III of EU ETS, excluding the test phase (I), and by considering the results in the new AB32.

5 FINAL REMARKS AND DIRECTIONS FOR FURTHER RESEARCH

In the current economic uncertainty context with climate change concerns, rise of primary energy prices, and numerous carbon markets that have multiplied around the world in recent years, there is an urge to develop quantitative tools that allow us to model and understand the origins and effects of variations in carbon prices. With this mission, this work answers to two major research questions about what causes changes in carbon prices, and what impacts those changes have on energy prices. It provides a complete and coherent analysis of carbon prices' variations vs. the role and effect of primary and final energies. Results have operational and political implications, highly relevant to main players in the market: polluters and regulators.

Previous research on carbon markets proliferated after EU ETS phase I (mostly published post 2009) and focussed on the study of the market itself, in aspects such as the sources of price variation, market design including allocation or offsets role, volatility, etc. Few have analysed both origins and implications of carbon prices in energy markets.

On the methodology, most preceding studies on carbon prices essentially explain the price or volatility of one variable in terms of others. This exogeneity assumption is very controversial in energy markets, so, to overcome this issue, we consider a multiple direction approach by developing a VAR model, and applying multivariate wavelet analysis. The use of VAR models for time series analysis is customary in macroeconomics or finance research (Silvestrini and Veredas 2008), but not in the analysis of energy vs carbon markets relation (García-Martos *et al.* 2013). There are only four studies that consider effects between variables – energy prices and carbon prices – in both directions. Fezzi and Bunn (2009) and Pinho and Madaleno (2011) both build a VECM that analyses mutual relationships between electricity, gas and carbon prices. However, the scope of the research by Fezzi and Bunn (2009) is gas, electricity and carbon prices in the United Kingdom. Pinho and Madaleno (2011), on another perspective, aim to analyse the effects on the energy-mix of several EU countries. Chevallier (2011d) builds a VAR Markov-Switching model, to analyse the connection between macroeconomics and carbon prices. And finally, García-Martos *et al.* (2013) build a conditionally heteroscedastic dynamic factor model and compare prediction accuracy between a multivariate and univariate model of energies, carbon, and offset prices, suggesting that the multivariate model improves forecasting accuracy. On another approach, Keppler and Mansanet-Bataller (2010) use repeated standard Granger causality tests to analyse carbon and energy prices causality. Although it is in its core an independent equations' analysis, the authors propose interesting causality connections between variables.

Building on preceding research on carbon prices, in particular in the above mentioned authors, our study makes a solid approach to the causes and effects of a carbon price and its variations. For that, we follow two complementary approaches: first we develop a VAR model, to capture multivariate interaction between variables, and second, we analyse the data in a time-frequency dimension, through multivariate wavelet analysis (MWA) tools recently developed by Aguiar-Conraria and Soares (2014). The MWA purpose is to analyse the correlation between the various prices at different frequencies. Energy price dynamics is nonstationary and so it is important to use methods that do not require stationarity. MWA tools allow to go beyond the study of daily cycles that the VAR allows, using an adequate methodology, indicative of existent relationships in other, longer, cycles than daily. We note that changes in power supply quantities, on a large scale, are neither easy nor quick. So, it makes sense to consider the presence of long-term decisions, or at lower frequencies, *i.e.*, correlations in longer temporal cycles. This information is retrieved by MWA, which also proposes causality indications that we compare with the VAR results. Also, to our knowledge, the MWA has never been applied before in any study.

Furthermore, previous research related to the development of carbon markets, mentioned throughout the chapters, only include EU ETS data for obvious availability reasons. This is a market characterized throughout its life by an oversupply of allowances. In this work, we additionally included the analysis of AB32, the Californian carbon market, for comparison and to assess more robust conclusions. Also, the vast majority of cases also includes data from EU ETS Phase I (2005-2007), the pre-Kyoto period, which we discarded, for consistency reasons. In short, the included endogenous variables were carbon prices, electricity prices (peak and baseload in EU), gas, coal, oil (CA only) and gasoline (CA only) prices, an economy performance index and CER prices (EU only).

From this work, we obtain a more comprehensive analysis of the interactions of energy and carbon markets than those presented in previous research, in particular Fezzi and Bunn (2009), Keppler and Mansanet-Bataller (2010), Chevallier (2011d), and García-Martos *et al.* (2013), the closest to the object of this work.

Our proposed hypothesis of **carbon price drivers** included positive immediate reactions from impacts of electricity and gasoline. This hypothesis is substantiated in the electricity analysis. No significant results are found regarding gasoline. The electricity has, however, an undeniable positive impact on carbon, for daily prices, immediate and permanent in the European case.

On primary energy, we hypothesized a positive connection originating from gas prices and negative from oil and coal. However, only oil showed permanent effects and influence in longer cycles. We also found evidence of the immediate and short-duration impact from gas and coal prices. This relation mostly occurs in California. The direction is the expected, from gas (positive) and oil (negative). However, the positive connection with coal comes by an indirect path via gas prices.

Regarding the existence of substitutes for carbon licences, we did not expect, nor did find, a significant effect on the carbon price.

On the economy role, we expected a positive, fast, reaction from the carbon market, which we found. However, the result is not as robust as anticipated because the impact does not have permanent effects in EU, and it is not significant in the AB32 study at any level. Nevertheless, it makes sense to be especially significant in the analysis of longer cycles, which we found in EU.

In short, our results showed us that electricity, gas, oil and the economy outdo other variables in explaining the variations of CO₂ prices, electricity and economy in Europe and gas and oil in California.

On **carbon price effects**, we hypothesized a positive relation from carbon to final energies, which we found in electricity at longer cycles (4~8 in AB32 and 8~10 in EU ETS). The impact is also visible in the EU ETS daily analysis, disappearing after the first days. As for gasoline, there is only an indication of causality in the California market, not sustained by any other analysis.

We also expected a negative relationship from carbon towards coal prices and positive relationship towards gas and oil. However, the only significant relation found was in the case of coal. This is visible in the Granger causality analysis in both markets and in the AB32 coal response, which we consider to be related to the inclusion of imported electricity per fuel. As expected, the relation is negative.

Also, results show us that there is no evidence that penalizing CO₂ emissions depleted economic activity in either market.

Finally, as hypothesized, we also found a positive impact of carbon prices from the EU ETS in offset prices (from emission reduction projects outside the EU ETS). As these licenses are substitutes of the EU ETS allowances to comply with the emission target, up to a limit of 10%, and are not recognized in any other market, the positive relationship found from the EUA to CER proves our initial hypothesis.

Briefly, **electricity, coal and CERs present evidence of the impact of variations in carbon price return rates.** The **economy does not present effects** of the carbon markets. Electricity effects are visible in both markets whereas coal effects are more evident in AB32. CERs were only analysed in EU ETS.

Our results have policy implications for both carbon markets. For the EU ETS, we propose that the market stability reserve percentage (currently 12%), should be reviewed yearly or, at least, every two years, to account for the effects observed of the carbon price in the electricity price, of coal and carbon relation, and finally, of the economy in the carbon price. The results also suggest that short cycle measures applied to the carbon market, such as the cancellation of a limited number of privately owned auctions, shouldn't have a significant effect in energy prices. Regarding the AB32 market, we expect gasoline prices to reflect the carbon price with more significance in future years. However, we advise against free allocation of licenses to fuel distributors in 2015, given the possible surplus of licenses in the market. Instead, we recommend costumers to save their 'climate credits' to accommodate the expected increase in gasoline and heating fuels prices.

On the main structural differences between the EU ETS and AB32 market, we consider that, in AB32, the carbon price contains more information on GHG emitting activities and allows consumers to be more aware of the cost of emissions. This happens because of the inclusion of fuels distributors, the accounting of electricity imports per fuel, the existence of a price floor and ceiling, and the return to consumers of the selling value of free allocated licences that have not been used. However, in EU ETS, the banking of licenses is not allowed between periods, while in AB32 is, which is not beneficial to the problem of overallocation. Both markets have aspects to learn from each other.

Comparing the overall EU and CA results obtained in our study, we note that the results of AB32 are dimmer than those of EU ETS. This evidence was expected, since the AB32 is extremely recent (2012), and we included data prior to its start. It will be interesting in future studies to verify the development of reactions of final energy to the price of carbon. Finally, regarding our study, the most inquisitive relationships that we found regard carbon-to-gas and carbon-to-coal prices. These relations will benefit from a deeper analysis when more data is available. Furthermore, in addition to the price analysis, we recommend that a market liquidity analysis via quantities of exchanged allowances would support this study. Unfortunately, at this time, the allowances volume data was not yet publicly available from stock exchanges.

It is also important to note that this study was conducted using data from 2008 to 2013, in Europe, meaning that the current economic and financial crisis may have had an influence. It will be interesting to complete this analysis with data from other carbon markets, namely with different economic conditions, such as the Chinese.

There are other interesting features that were not addressed by this study because they do not relate directly to the goal of our research. Nevertheless, they are central enough to be noted as subject for further studies. Transversely, future work may include analysis of the implications that arise on structural differences between the European and Californian carbon markets. Specifically, the analysis of the impact of the existence of upper and lower limits for carbon prices in AB32, unlike in the EU ETS, in the price differential between the two markets, and the effect that may have on prices of final and primary energy. Moreover, the impact on the European carbon price of considering electricity imports emissions, by source, and of fossil fuel distributors' emissions regarding the transport sector. On another view, the linkage of markets happening now, namely the connection established between the AB32 and Québec in January 2014 and the possible future link of the EU ETS to the Australian market, may also bring consequences to the price of carbon.

Finally, our results should also experience modifications in the case of technology developments, namely in carbon capture and storage, because the emission factor of a power plant equipped with this technology will be much less than the standard EF considered. Currently there are only pilot projects operating, so, to study its impact is our last recommendation for further studies.

On stakeholders' interests, the presented results and methodology have tangible utility for companies under emission limits, for financial traders involved in carbon markets, for carbon and energy regulators, and also for consumers of energy intensive goods. Main practical applications include portfolio optimization for utilities, development of hedging strategies in energy and carbon markets, and market regulation and enhancement. Knowledge on origins and effects of carbon prices will improve the quality in decision making of all parties involved.

To conclude, the obtained results allow further knowledge on carbon markets and enhance previous research in three perspectives: first, we present a complete analysis of the multivariate relationship between energy prices and carbon, considering effects of the economy and temperature. Second, we study effects on different frequencies that a single multivariate analysis

does not show, using an innovative application of wavelets simultaneously to carbon and energy markets. And finally, third, we consider more consistent information about carbon markets, by including phase III of the European market, excluding the test phase (I), and by considering the results of the new California carbon market.

Among previously referred specific conclusions, **we finalize stating that electricity, gas, oil and the economy drive variations of CO₂ prices, and CO₂ prices are impacting electricity mostly in longer cycles and coal, in daily analysis, but with very short-timed effects.** This is valuable knowledge that will improve decision making quality of all parties involved in energy and carbon markets.

BIBLIOGRAPHY

- AAAS (2009). *Statement on climate change from 18 scientific associations. Letter to US Senator*. US, American Association for the Advancement of Science, http://www.aaas.org/sites/default/files/migrate/uploads/1021climate_letter1.pdf, accessed 01/02/2014.
- Aatola, P., Ollikainen, M. and Toppinen, A. (2013a). *Impact of the carbon price on the integrating European electricity market*. Energy Policy **61**: 1236-1251.
- Aatola, P., Ollikainen, M. and Toppinen, A. (2013b). *Price determination in the EU ETS market: Theory and econometric analysis with market fundamentals*. Energy Economics **36**: 380-395.
- Abadie, L. and Chamorro, J. (2008). *Carbon price risk and the clean dark spread*. 3rd Atlantic Workshop on Energy and Environmental Economics, Toxa, Spain.
- AGU (2013). *Human-Induced Climate Change Requires Urgent Action. AGU Climate Change Position Statement*. US, American Geophysical Union, http://sciencepolicy.agu.org/files/2013/07/AGU-Climate-Change-Position-Statement_August-2013.pdf, accessed 01/02/2014.
- Aguiar-Conraria, L., Azevedo, N. and Soares, M. J. (2008). *Using wavelets to decompose the time-frequency effects of monetary policy*. Physica A: Statistical Mechanics and its Applications **387**(12): 2863-2878.
- Aguiar-Conraria, L. and Soares, M. J. (2011a). *Business cycle synchronization and the Euro: a wavelet analysis*. Journal of Macroeconomics **33**(3): 477-489.
- Aguiar-Conraria, L. and Soares, M. J. (2011b). *Oil and the macroeconomy: using wavelets to analyze old issues*. Empirical Economics **40**(3): 645-655.
- Aguiar-Conraria, L. and Soares, M. J. (2014). *The continuous wavelet transform: moving beyond uni- and bivariate analysis*. Journal of Economic Surveys **28**(2): 344-375.
- Alberola, E. and Chevallier, J. (2009). *European Carbon Prices and Banking Restrictions: Evidence from Phase I (2005-2007)*. Energy Journal **30**(3): 51-79.
- Alberola, E., Chevallier, J. and Cheze, B. (2008). *Price drivers and structural breaks in European carbon prices 2005-2007*. Energy Policy **36**(2): 787-797.
- Alberola, E., Chevallier, J. and Cheze, B. (2009a). *Emissions Compliances and Carbon Prices under the EU ETS: A Country Specific Analysis of Industrial Sectors*. Journal of Policy Modeling **31**(3): 446-462.
- Alberola, E., Chevallier, J. and Chèze, B. (2009b). *The EU emissions trading scheme: The effects of industrial production and CO₂ emissions on carbon prices*. Economie internationale **116**(4): 93-125.
- Aloui, C. and Hkiri, B. (2014). *Co-movements of GCC emerging stock markets: New evidence from wavelet coherence analysis*. Economic Modelling **36**: 421-431.

- Alvarez-Ramirez, J., Rodriguez, E. and Espinosa-Paredes, G. (2012). *A partisan effect in the efficiency of the US stock market*. *Physica A: Statistical Mechanics and its Applications* **391**(20): 4923-4932.
- Amisano, G. and Giannini, C. (1997). *From VAR models to Structural VAR models*. *Topics in Structural VAR Econometrics*, Springer-Verlag GmbH: 1-28.
- Arouri, M. E. H., Jawadi, F. and Nguyen, D. K. (2012). *Nonlinearities in carbon spot-futures price relationships during Phase II of the EU ETS*. *Economic Modelling* **29**(3): 884-892.
- Asafu-Adjaye, J. (2000). *The relationship between energy consumption, energy prices and economic growth: time series evidence from Asian developing countries*. *Energy Economics* **22**(6): 615-625.
- Baubeau, P. and Cazelles, B. (2009). *French economic cycles: a wavelet analysis of French retrospective GNP series*. *Clometrica* **3**(3): 275-300.
- Baumol, W. J. and Oates, W. E. (1971). *The use of standards and prices for protection of the environment*. *The Swedish Journal of Economics* **3**(1): 42-54.
- Benz, E. and Truck, S. (2009). *Modeling the price dynamics of CO2 emission allowances*. *Energy Economics* **31**(1): 4-15.
- Blanchard, J. and Quah, D. (1989). *The Dynamic Effects of Aggregate Demand and Supply Disturbances*. *The American Economic Review* **79**(4): 655-673.
- Bloomfield, P. (2004). *Fourier analysis of time series: an introduction*, John Wiley & Sons.
- Blyth, W., Bunn, D., Kettunen, J. and Wilson, T. (2009). *Policy interactions, risk and price formation in carbon markets*. *Energy Policy* **37**(12): 5192-5207.
- Bonenti, F., Oggioni, G., Allevi, E. and Marangoni, G. (2013). *Evaluating the EU ETS impacts on profits, investments and prices of the Italian electricity market*. *Energy Policy* **59**: 242-256.
- Branger, F., Lecuyer, O. and Quirion, P. (2013). *The European Union Emissions Trading System: should we throw the flagship out with the bathwater?* *CIRE Working Papers Series* **48**.
- Bredin, D. and Muckley, C. (2011). *An emerging equilibrium in the EU emissions trading scheme*. *Energy Economics* **33**(2): 353-362.
- Broock, W. A., Scheinkman, J. A., Dechert, W. D. and LeBaron, B. (1996). *A test for independence based on the correlation dimension*. *Econometric Reviews* **15**(3): 197-235.
- Burton, E. S., Pechan, E. H. and Sanjour, W. (1973). *Solving the air pollution control puzzle*. *Environmental Science & Technology* **7**(5): 412-415.
- Burton, E. S. and Sanjour, W. (1970). *A simulation approach to air pollution abatement program planning*. *Socio-Economic Planning Sciences* **4**(1): 147-159.
- Bushnell, J. and Chen, Y. (2012). *Allocation and leakage in regional cap-and-trade markets for CO2*. *Resource and Energy Economics* **34**(4): 647-668.

- Bushnell, J., Chen, Y. and Zaragoza-Watkins, M. (2014). *Downstream regulation of CO2 emissions in California's electricity sector*. Energy Policy **64**: 313-323.
- Bushnell, J. B. (2007). *The Implementation of California AB 32 and its Impact on Wholesale Electricity Markets*. CSEM Working Paper **170**.
- Byun, S. J. and Cho, H. (2013). *Forecasting carbon futures volatility using GARCH models with energy volatilities*. Energy Economics **40**: 207-221.
- Calel, R. (2011). *Climate change and carbon markets: a panoramic history*. Grantham Research Institute on Climate Change and the Environment - Working Paper **52**.
- Caraiani, P. (2012). *Stylized facts of business cycles in a transition economy in time and frequency*. Economic Modelling **29**(6): 2163-2173.
- Carmona, R., Fehr, M. and Hinz, J. (2009). *Optimal Stochastic Control and Carbon Price Formation*. Siam Journal on Control and Optimization **48**(4): 2168-2190.
- Charles, A., Darné, O. and Fouilloux, J. (2013). *Market efficiency in the European carbon markets*. Energy Policy **60**(C): 785-792.
- Chen, D. P. and Bunn, D. W. (2010). *Analysis of the Nonlinear Response of Electricity Prices to Fundamental and Strategic Factors*. IEEE Transactions on Power Systems **25**(2): 595-606.
- Chen, Y., Liu, A. L. and Hobbs, B. F. (2011). *Economic and Emissions Implications of Load-Based, Source-Based, and First-Seller Emissions Trading Programs Under California AB32*. Operations research **59**(3): 696-712.
- Chevallier, J. (2009). *Carbon futures and macroeconomic risk factors: A view from the EU ETS*. Energy Economics **31**(4): 614-625.
- Chevallier, J. (2010). *Modelling risk premia in CO2 allowances spot and futures prices*. Economic Modelling **27**(3): 717-729.
- Chevallier, J. (2011a). *Carbon price drivers: an updated literature review*. SSRN Working Paper **1811963**.
- Chevallier, J. (2011b). *Detecting instability in the volatility of carbon prices*. Energy Economics **33**(1): 99-110.
- Chevallier, J. (2011c). *Macroeconomics, finance, commodities: Interactions with carbon markets in a data-rich model*. Economic Modelling **28**(1-2): 557-567.
- Chevallier, J. (2011d). *A model of carbon price interactions with macroeconomic and energy dynamics*. Energy Economics **33**(6): 1295-1312.
- Chevallier, J. (2013). *Variance risk-premia in CO2 markets*. Economic Modelling **31**(0): 598-605.
- Chevallier, J. and Sévi, B. (2010). *On the realized volatility of the ECX CO2 emissions 2008 futures contract: distribution, dynamics and forecasting*. Fondazione Eni Enrico Mattei Working Paper **377**.

- Christiansen, A. C., Arvanitakis, A., Tangen, K. and Hasselknippe, H. (2005). *Price determinants in the EU emissions trading scheme*. *Climate Policy* **5**(1): 15-30.
- Cohen, E. A. and Walden, A. T. (2010). *A statistical study of temporally smoothed wavelet coherence*. *Signal Processing, IEEE Transactions on* **58**(6): 2964-2973.
- Connor, J. and Rossiter, R. (2005). *Wavelet transforms and commodity prices*. *Studies in Nonlinear Dynamics & Econometrics* **9**(1).
- Conrad, C., Rittler, D. and Rotfuß, W. (2012). *Modeling and explaining the dynamics of European Union Allowance prices at high-frequency*. *Energy Economics* **34**(1): 316-326.
- Creti, A., Jouvet, P.-A. and Mignon, V. (2012). *Carbon price drivers: Phase I versus Phase II equilibrium?* *Energy Economics* **34**(1): 327-334.
- Crocker, T. D. (1966). *The structuring of atmospheric pollution control systems. The economics of air pollution*. H. Wlozin. New York, W. W. Norton & Co.: 61-86.
- Crowley, P. M. (2007). *A guide to wavelets for economists*. *Journal of Economic Surveys* **21**(2): 207-267.
- Dales, J. H. (1968). *Pollution, property and prices: An essay in policy-making and economics*, University of Toronto Press.
- Daskalakis, G., Psychoyios, D. and Markellos, R. N. (2009). *Modeling CO2 emission allowance prices and derivatives: Evidence from the European trading scheme*. *Journal of Banking & Finance* **33**(7): 1230-1241.
- Declercq, B., Delarue, E. and D'haeseleer, W. (2011). *Impact of the economic recession on the European power sector's CO2 emissions*. *Energy Policy* **39**(3): 1677-1686.
- Demailly, D. and Quirion, P. (2008). *European Emission Trading Scheme and competitiveness: A case study on the iron and steel industry*. *Energy Economics* **30**(4): 2009-2027.
- Deng, S.-J. (2005). *Valuation of investment and opportunity-to-invest in power generation assets with spikes in electricity price*. *Managerial Finance* **31**(6): 95-115.
- Denny, E. and O'Malley, M. (2009). *The impact of carbon prices on generation-cycling costs*. *Energy Policy* **37**(4): 1204-1212.
- Dickey, D. A. and Fuller, W. A. (1979). *Distribution of the estimators for autoregressive time series with a unit root*. *Journal of the American Statistical Association* **74**(366a): 427-431.
- Domanico, F. (2007). *Concentration in the European electricity industry: The internal market as solution?* *Energy Policy* **35**(10): 5064-5076.
- Durand-Lasserve, O., Pierru, A. and Smeers, Y. (2011). *Effects of the uncertainty about global economic recovery on energy transition and CO2 price*. MIT CEEPR Working Paper **2011-005**.
- EC (2013a). *Consequences of climate change*. E. Commission, European Commission, http://ec.europa.eu/clima/policies/brief/consequences/index_en.htm, accessed 12/12/2013.

- EC (2013b). *EU ETS Factsheet*. E. Commission, European Commission, <http://ec.europa.eu/clima/policies/ets/>, accessed 12/12/2013.
- EC (2014), *2030 climate and energy goals for a competitive, secure and low-carbon EU economy*. 22/01/2014 - COM(2014) 15, European Commission
- Egenhofer, C. and Alessi, M. (2013). *EU policy on climate change mitigation since Copenhagen and the economic crisis*. CEPS Working Document **380**.
- Ellerman, A. D. and Harrison Jr, D. (2003). *Emissions trading in the US: Experience, lessons, and considerations for greenhouse gases*, PEW Center on Global Climate Change.
- Enders, W. (2008). *Applied econometric time series*, John Wiley & Sons.
- EPA (2007), *Acid Rain and Related Programs - 2007 Progress Report*. EPA
- Fan, Y. and Gençay, R. (2010). *Unit root tests with wavelets*. *Econometric Theory* **26**(05): 1305-1331.
- Farge, M. (1992). *Wavelet transforms and their applications to turbulence*. *Annual Review of Fluid Mechanics* **24**(1): 395-458.
- Fell, H. (2010). *EU-ETS and Nordic Electricity: A CVAR Analysis*. *Energy Journal* **31**(2).
- Feng, Z.-H., Wei, Y.-M. and Wang, K. (2012). *Estimating risk for the carbon market via extreme value theory: An empirical analysis of the EU ETS*. *Applied Energy* **99**: 97-108.
- Feng, Z. H., Zou, L. L. and Wei, Y. M. (2011). *Carbon price volatility: Evidence from EU ETS*. *Applied Energy* **88**(3): 590-598.
- Fernández-Macho, J. (2012). *Wavelet multiple correlation and cross-correlation: A multiscale analysis of Eurozone stock markets*. *Physica A: Statistical Mechanics and its Applications* **391**(4): 1097-1104.
- Fernandez, V. P. (2005). *The international CAPM and a wavelet-based decomposition of value at risk*. *Studies in Nonlinear Dynamics & Econometrics* **9**(4).
- Fezzi, C. and Bunn, D. W. (2009). *Structural interactions of European carbon trading and energy prices*. *The Journal of Energy Markets* **2**(4): 53-69.
- Fine, J., Busch, C. and Garderet, R. (2012). *The upside hedge value of California's global warming policy given uncertain future oil prices*. *Energy Policy* **44**: 46-51.
- Fischer, C., Kerr, S. and Toman, M. (1998). *Using emissions trading to regulate US greenhouse gas emissions: An overview of policy design and implementation issues*. *National Tax Journal* **51**: 453-464.
- Fuss, S. and Szolgayová, J. (2010). *Fuel price and technological uncertainty in a real options model for electricity planning*. *Applied Energy* **87**(9): 2938-2944.
- Gabor, D. (1946). *Theory of communication*. *Journal of the Institute of Electrical Engineers* **93**: 429-457.

- Gallegati, M. (2008). *Wavelet analysis of stock returns and aggregate economic activity*. Computational Statistics & Data Analysis **52**(6): 3061-3074.
- Gallegati, M., Gallegati, M., Ramsey, J. B. and Semmler, W. (2011). *The US Wage Phillips Curve across Frequencies and over Time*. Oxford Bulletin of Economics and Statistics **73**(4): 489-508.
- García-Martos, C., Rodríguez, J. and Sánchez, M. J. (2011). *Forecasting electricity prices and their volatilities using Unobserved Components*. Energy Economics **33**(6): 1227-1239.
- García-Martos, C., Rodríguez, J. and Sánchez, M. J. (2013). *Modelling and forecasting fossil fuels, CO₂ and electricity prices and their volatilities*. Applied Energy **101**: 363-375.
- Ge, Z. (2008). *Significance tests for the wavelet cross spectrum and wavelet linear coherence*. Annales Geophysicae, Copernicus GmbH.
- Geman, H. (2009). *Commodities and commodity derivatives: modeling and pricing for agriculturals, metals and energy*, John Wiley & Sons.
- Gençay, R., Selçuk, F. and Whitcher, B. (2005). *Multiscale systematic risk*. Journal of International Money and Finance **24**(1): 55-70.
- Gençay, R., Selçuk, F. and Whitcher, B. (2001a). *Scaling properties of foreign exchange volatility*. Physica A: Statistical Mechanics and its Applications **289**(1): 249-266.
- Gençay, R., Selçuk, F. and Whitcher, B. J. (2001b). *An introduction to wavelets and other filtering methods in finance and economics*. San Diego, CA, Academic press.
- Gencay, R. and Signori, D. (2012). *Multi-scale tests for serial correlation*. Department of Economics, Simon Fraser University **Technical report**.
- Gerace, M. P. (2002). *US military expenditures and economic growth: some evidence from spectral methods*. Defence and Peace Economics **13**(1): 1-11.
- Goldstein, J. S. (1988). *Long cycles: prosperity and war in the modern age*, Yale University Press New Haven.
- Gorenflo, M. (2012). *Futures price dynamics of CO₂ emission allowances*. Empirical Economics: 1-23.
- Goupillaud, P., Grossmann, A. and Morlet, J. (1984). *Cycle-octave and related transforms in seismic signal analysis*. Geoexploration **23**(1): 85-102.
- Granger, C. W. (1969). *Investigating causal relations by econometric models and cross-spectral methods*. Econometrica **37**: 424-438.
- Granger, C. W. J. (1966). *The typical spectral shape of an economic variable*. Econometrica **34**(1): 150-161.
- Gronwald, M., Ketterer, J. and Truck, S. (2011). *The relationship between carbon, commodity and financial markets: a copula analysis*. Economic Record **87**: 105-124.

- Gulli, F. (2008). *Modelling the short run impact of "carbon trading" on the electricity sector*. Markets For Carbon and Power Pricing in Europe: Theoretical Issues and Empirical Analyses: 145-159.
- Hauch, J. (2003). *Electricity trade and CO2 emission reductions in the Nordic countries*. Energy Economics **25**(5): 509-526.
- Helm, D. (2005). *Economic instruments and environmental policy*. Economic and Social Review **36**(3): 205.
- Hintermann, B. (2010). *Allowance price drivers in the first phase of the EU ETS*. Journal of Environmental Economics and Management **59**(1): 43-56.
- Hobbs, B. F., Bushnell, J. and Wolak, F. A. (2010). *Upstream vs. downstream CO2 trading: A comparison for the electricity context*. Energy Policy **38**(7): 3632-3643.
- Hocaoglu, F. O. and Karanfil, F. (2011). *Examining the link between carbon dioxide emissions and the share of industry in GDP: Modeling and testing for the G-7 countries*. Energy Policy **39**(6): 3612-3620.
- Huntington, H. G. and Weyant, J. P. (2004). *Modeling Energy Markets and Climate Change Policy*. Encyclopedia of Energy. C. J. Cleveland. New York, Elsevier: 41-53.
- IPCC (2007). *Climate Change 2007: Synthesis Report - Contribution of Working Groups I, II and III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*. R. K. Pachauri, Reisinger, A. . Geneva, Switzerland. , IPCC.
- IPCC (2013). *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* T. F. Stocker, D. Qin, G.-K. Plattner et al. Cambridge, United Kingdom and New York, USA.
- Jammazi, R. (2012). *Cross dynamics of oil-stock interactions: A redundant wavelet analysis*. Energy **44**(1): 750-777.
- Jouvet, P.-A. and Solier, B. (2013). *An overview of CO2 cost pass-through to electricity prices in Europe*. Energy Policy **61**(0): 1370-1376.
- Kara, M., Syri, S., Lehtilä, A., Helynen, S., Kekkonen, V., Ruska, M. and Forsström, J. (2008). *The impacts of EU CO2 emissions trading on electricity markets and electricity consumers in Finland*. Energy Economics **30**(2): 193-211.
- Keppler, J. H. and Cruciani, M. (2010). *Rents in the European power sector due to carbon trading*. Energy Policy **38**(8): 4280-4290.
- Keppler, J. H. and Mansanet-Bataller, M. (2010). *Causalities between CO2, electricity, and other energy variables during phase I and phase II of the EU ETS*. Energy Policy **38**(7): 3329-3341.
- Kim, W., Chattopadhyay, D. and Park, J.-b. (2010). *Impact of carbon cost on wholesale electricity price: A note on price pass-through issues*. Energy **35**(8): 3441-3448.
- Kirat, D. and Ahamada, I. (2011). *The impact of the European Union emission trading scheme on the electricity-generation sector*. Energy Economics **33**(5): 995-1003.

- Koch, N. (2014). *Dynamic linkages among carbon, energy and financial markets: a smooth transition approach*. *Applied Economics* **46**(7): 715-729.
- Kopp, R. and Mignone, B. (2013). *Circumspection, reciprocity, and optimal carbon prices*. *Climatic Change* **120**(4): 831-843.
- Kumar, S., Managi, S. and Matsuda, A. (2012). *Stock prices of clean energy firms, oil and carbon markets: A vector autoregressive analysis*. *Energy Economics* **34**(1): 215-226.
- Kury, T. J. and Harrington, J. (2010). *The Marginal Effects of the Price for Carbon Dioxide: Quantifying the Effects on the Market for Electric Generation in Florida*. *The Electricity Journal* **23**(4): 73-78.
- Kyrtsoy, C., Malliaris, A. G. and Serletis, A. (2009). *Energy sector pricing: On the role of neglected nonlinearity*. *Energy Economics* **31**(3): 492-502.
- Lanzi, E., Chateau, J. and Dellink, R. (2012). *Alternative approaches for levelling carbon prices in a world with fragmented carbon markets*. *Energy Economics* **34**, **Supplement 2**: S240-S250.
- Laurikka, H. and Koljonen, T. (2006). *Emissions trading and investment decisions in the power sector—a case study in Finland*. *Energy Policy* **34**(9): 1063-1074.
- Li, T., Zhang, Z. G. and Zhao, L. T. (2013). *Estimating the portfolio risk with copula-GARCH-EVT method: empirical study of carbon market*. *Advanced Materials Research* **791**: 2175-2178.
- Linares, P., Santos, F. J., Ventosa, M. and Lapiedra, L. (2006). *Impacts of the European Emissions Trading Scheme Directive and Permit Assignment Methods on the Spanish Electricity Sector*. *Energy Journal* **27**(1).
- Liu, H.-H. and Chen, Y.-C. (2013). *A study on the volatility spillovers, long memory effects and interactions between carbon and energy markets: The impacts of extreme weather*. *Economic Modelling* **35**(0): 840-855.
- Löfgren, Å., Wråke, M., Hagberg, T. and Roth, S. (2013). *Why the EU ETS needs reforming: an empirical analysis of the impact on company investments*. *Climate Policy*: 1-22.
- Lundgren, T., Marklund, P.-O., Samakovlis, E. and Zhou, W. (2013). *Carbon prices and incentives for technological development*. *CERE Working Paper* **2013:4**.
- Lutz, B. J., Pigorsch, U. and Rotfuß, W. (2013). *Nonlinearity in cap-and-trade systems: The EUA price and its fundamentals*. *Energy Economics* **40**: 222-232.
- MacKinnon, J. G. (1996). *Numerical distribution functions for unit root and cointegration tests*. *Journal of Applied Econometrics* **11**: 601-618.
- Mansanet-Bataller, M., Chevallier, J., Hervé-Mignucci, M. and Alberola, E. (2011). *EUA and sCER phase II price drivers: Unveiling the reasons for the existence of the EUA–sCER spread*. *Energy Policy* **39**(3): 1056-1069.
- Mansanet-Bataller, M., Pardo, A. and Valor, E. (2007). *CO₂ prices, energy and weather*. *Energy Journal* **28**(3): 73-92.

- Mansanet-Bataller, M. and Soriano, P. (2009). *Volatility transmission in the CO₂ and energy markets*. 6th International Conference on the European Energy Market, Leuven, University of Leuven.
- Medina, V., Pardo, Á. and Pascual, R. (2014). *The timeline of trading frictions in the european carbon market*. *Energy Economics* **42**: 378–394.
- Meehl, G. A. and al, e. (2007). *2007: Global Climate Projections*. In: *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change IPCC AR4 IPCC*, IPCC.
- Metz, B. and al, e. (2001). *Chapter 6. Policies, Measures, and Instruments - "6.1.5.1 Key Lessons from the Political Economy Literature."* *Climate Change 2001: Mitigation. Contribution of Working Group III to the Third Assessment Report of the Intergovernmental Panel on Climate Change. IPCC TAR*. IPCC. N.Y., IPCC.
- Milunovich, G. J., Roselyne (2007). *Testing Market Efficiency and Price Discovery in European Carbon Markets*. Macquarie University Working Paper.
- Naccache, T. (2011). *Oil price cycles and wavelets*. *Energy Economics* **33**(2): 338-352.
- Napolitano, S., Schreifels, J., Stevens, G., Witt, M., LaCount, M., Forte, R. and Smith, K. (2007). *The US acid rain program: key insights from the design, operation, and assessment of a cap-and-trade program*. *The Electricity Journal* **20**(7): 47-58.
- NAS, N. A. o. S.-. (2005). *Global response to climate change. Joint science academies' statement*. C. National Academies of Sciences of Brazil, China, France, Germany, India, Italy, Japan, Russia, United Kingdom and the United States of America, <http://www.nationalacademies.org/onpi/06072005.pdf>, accessed 01/02/2014.
- Näsäkkälä, E. and Fleten, S.-E. (2005). *Flexibility and technology choice in gas fired power plant investments*. *Review of Financial Economics* **14**(3–4): 371-393.
- Nazifi, F. (2013). *Modelling the price spread between EUA and CER carbon prices*. *Energy Policy* **56**: 434-445.
- Oberndorfer, U. (2009). *EU Emission Allowances and the stock market: Evidence from the electricity industry*. *Ecological Economics* **68**(4): 1116-1126.
- Palao, F. and Pardo, A. (2012). *Assessing price clustering in European Carbon Markets*. *Applied Energy* **92**: 51-56.
- Peace, J. and Juliani, T. (2009). *The coming carbon market and its impact on the American economy*. *Policy and Society* **27**(4): 305-316.
- Peña, D., Tiao, G. C. and Tsay, R. S. (2011). *A course in time series analysis*, John Wiley & Sons.
- Pigou, A. C. (1924). *The economics of welfare*, Transaction Publishers.
- Pinho, C. and Madaleno, M. (2011). *CO₂ emission allowances and other fuel markets interaction*. *Environmental Economics and Policy Studies* **13**(3): 259-281.
- Priestley, M. B. (1982). *Spectral analysis and time series*. San Diego, CA., Academic Press.

- Ramsey, J. B. and Lampart, C. (1998a). *The decomposition of economic relationships by time scale using wavelets: expenditure and income*. Studies in Nonlinear Dynamics and Econometrics **3**(1): 23-42.
- Ramsey, J. B. and Lampart, C. (1998b). *Decomposition of economic relationships by timescale using wavelets*. Macroeconomic dynamics **2**(1): 49-71.
- Reboredo, J. C. (2014). *Volatility spillovers between the oil market and the European Union carbon emission market*. Economic Modelling **36**: 229-234.
- Reboredo, J. C. and Rivera-Castro, M. A. (2014). *Wavelet-based evidence of the impact of oil prices on stock returns*. International Review of Economics & Finance **29**: 145-176.
- Reinaud, J. (2007). *CO2 allowance and electricity price interaction: impact on industry's electricity purchasing strategies in Europe*. Information Paper. IEA. Paris.
- Richards, D. (1992). *Spatial correlation test for chaotic dynamics in political science*. American Journal of Political Science **36**(4): 1047-1069.
- Rittler, D. (2012). *Price discovery and volatility spillovers in the European Union emissions trading scheme: A high-frequency analysis*. Journal of Banking & Finance **36**(3): 774-785.
- Roques, F. A., Newbery, D. M. and Nuttall, W. J. (2008). *Fuel mix diversification incentives in liberalized electricity markets: A Mean–Variance Portfolio theory approach*. Energy Economics **30**(4): 1831-1849.
- Rua, A. (2012). *Money Growth and Inflation in the Euro Area: A Time-Frequency View*. Oxford Bulletin of Economics and Statistics **74**(6): 875-885.
- Rua, A. and Nunes, L. C. (2009). *International comovement of stock market returns: A wavelet analysis*. Journal of Empirical Finance **16**(4): 632-639.
- Scheepers, M., Wals, A. and Rijkers, F. (2003). *Position of large power producers in electricity markets of north Western Europe*. Draft Rep. ECN-C-03-003, Amsterdam, The Netherlands.
- Schumpeter, J. (1933). *The Common Sense of Econometrics*. Econometrica **1**(1): 5-12.
- Seifert, J., Uhrig-Homburg, M. and Wagner, M. (2008). *Dynamic behavior of CO2 spot prices*. Journal of Environmental Economics and Management **56**(2): 180-194.
- Sheppard, L., Stefanovska, A. and McClintock, P. (2012). *Testing for time-localized coherence in bivariate data*. Physical Review E **85**(4): 046205.
- Sijm, J., Chen, Y. and Hobbs, B. F. (2012). *The impact of power market structure on CO2 cost pass-through to electricity prices under quantity competition – A theoretical approach*. Energy Economics **34**(4): 1143-1152.
- Sijm, J., Neuhoﬀ, K. and Chen, Y. (2006). *CO2 cost pass-through and windfall profits in the power sector*. Climate Policy **6**(1): 49-72.
- Silvestrini, A. and Veredas, D. (2008). *Temporal aggregation of univariate and multivariate time series models: a survey*. Journal of Economic Surveys **22**(3): 458-497.

- Sims, C. A. (1980). *Macroeconomics and Reality*. *Econometrica* **48**(1): 1-48.
- Sivaraman, D. and Moore, M. R. (2012). *Economic performance of grid-connected photovoltaics in California and Texas (United States): The influence of renewable energy and climate policies*. *Energy Policy* **49**: 274-287.
- Smale, R., Hartley, M., Hepburn, C., Ward, J. and Grubb, M. (2006). *The impact of CO₂ emissions trading on firm profits and market prices*. *Climate Policy* **6**(1): 31-48.
- Smith, S. (2008). *Environmentally related taxes and tradable permit systems in practice*. Environment Directorate, OECD, Paris.
- Springer, U. and Varilek, M. (2004). *Estimating the price of tradable permits for greenhouse gas emissions in 2008-12*. *Energy Policy* **32**(5): 611-621.
- Stern, D. (2011). *From Correlation to Granger Causality*. Crawford School Research Paper(13).
- Stern, N. (2006). *Review on the economics of climate change*. London HM Treasury.
- Stock, J. and Watson, M. (2001). *Notes on Vector Autoregressions*. *Econometric Theory II: Time Series*, Harvard University, Cambridge, Massachusetts,
http://faculty.washington.edu/ezivot/econ584/stck_watson_var.pdf, accessed 01/02/2014.
- Thurber, M. C. and Wolak, F. A. (2013). *Carbon in the Classroom: Lessons from a Simulation of California's Electricity Market Under a Stringent Cap-and-Trade System*. *The Electricity Journal* **26**(7): 8-21.
- Tiao, G. C. and Tsay, R. S. (1989). *Model specification in multivariate time series*. *Journal of the Royal Statistical Society. Series B (Methodological)*: 157-213.
- Tietenberg, T. (1985). *Emissions trading: An exercise in reforming pollution policy*, RFF Press.
- Tietenberg, T. (2003). *The tradable-permits approach to protecting the commons: Lessons for climate change*. *Oxford Review of Economic Policy* **19**(3): 400-419.
- Tietenberg, T. (2010). *The evolution of emissions trading*. *Better Living Through Economics*: 42-58.
- Tietenberg, T. and Lewis, L. (2009). *Environmental & Natural Resources Economics, 8th ed.* Boston, Pearson International.
- Tindale, S. (2013). *Saving emissions trading from irrelevance*. *Think Global*. CER, Centre for European Reform.
- Tiwari, A. K., Mutascu, M. I. and Albulescu, C. T. (2013). *The influence of the international oil prices on the real effective exchange rate in Romania in a wavelet transform framework*. *Energy Economics* **40**: 714-733.
- Tolis, A. I. and Rentizelas, A. A. (2011). *An impact assessment of electricity and emission allowances pricing in optimised expansion planning of power sector portfolios*. *Applied Energy* **88**(11): 3791-3806.

- Torrence, C. and Compo, G. P. (1998). *A practical guide to wavelet analysis*. Bulletin of the American Meteorological society **79**(1): 61-78.
- Tsay, R. S. (2010). *Analysis of financial time series*, John Wiley & Sons.
- UNFCCC (1992), *United Nations Framework Convention on Climate Change*. FCCC/INFORMAL/84 , GE.05-62220 (E) 200705, United Nations
- UNFCCC (2007). *Climate change science. Essential background*, UNFCCC, https://unfccc.int/essential_background/the_science/items/6064.php, accessed 10/02/2014.
- Vacha, L. and Barunik, J. (2012). *Co-movement of energy commodities revisited: Evidence from wavelet coherence analysis*. Energy Economics **34**(1): 241-247.
- Vacha, L., Janda, K., Kristoufek, L. and Zilberman, D. (2013). *Time–frequency dynamics of biofuel–fuel–food system*. Energy Economics **40**: 233-241.
- Voß, J.-P. (2007). *Innovation processes in governance: the development of ‘emissions trading’ as a new policy instrument*. Science and Public Policy **34**(5): 329-343.
- Wen, Y. (2005). *Understanding the inventory cycle*. Journal of Monetary Economics **52**(8): 1533-1555.
- Widerberg, A. and Wråke, M. (2009). *The impact of the EU emissions trading system on CO2 intensity in electricity generation*. University of Gothenburg Working Papers in Economics **361**.
- Wolak, F. A. (2003). *Diagnosing the California Electricity Crisis*. The Electricity Journal **16**(7): 11-37.
- Wong, H., Ip, W.-C., Xie, Z. and Lui, X. (2003). *Modelling and forecasting by wavelets, and the application to exchange rates*. Journal of Applied Statistics **30**(5): 537-553.
- Zachmann, G. and von Hirschhausen, C. (2008). *First evidence of asymmetric cost pass-through of EU emissions allowances: Examining wholesale electricity prices in Germany*. Economics Letters **99**(3): 465-469.
- Zhang, Y.-J. and Wei, Y.-M. (2010). *An overview of current research on EU ETS: Evidence from its operating mechanism and economic effect*. Applied Energy **87**(6): 1804-1814.
- Zhu, B., Ma, S., Chevallier, J. and Wei, Y. (2014). *Modelling the dynamics of European carbon futures price: A Zipf analysis*. Economic Modelling **38**(0): 372-380.
- Zhu, B. and Wei, Y. (2013). *Carbon price forecasting with a novel hybrid ARIMA and least squares support vector machines methodology*. Omega **41**(3): 517-524.
- Zhuang, D. D. (2013). *Tail dependence structure between carbon emission allowances returns based on copulas*. Applied Mechanics and Materials **397**: 726-730.

APPENDIX - DATA OUTPUT AND ECONOMETRIC TESTS

A European data

A.1 Econometric data tests

Stationarity data analysis

Below we present the results of unit root testing. We use the Augmented Dickey-Fuller test (Dickey and Fuller 1979) , with the MacKinnon (1996) one-sided p-values. For lag selection we consider the Akaike Info Criterion.

Variable (levels)	Integration order	Differentiated variable ADF t-stat
log(CO2)	I(1)	-8.587657
log(CER)	I(1)	-7.315691
log(ele_p)	I(1)	-34.71840
log(ele_b)	I(1)	-26.61462
log(gas)	I(1)	-12.93957
log(coal)	I(1)	-7.912795
log(econ)	I(1)	-18.93649

Other unit root tests such as Phillips-Perron (1988) and Kwiatkowski, Phillips, Schmidt, and Shin (KPSS, 1992) yield similar results at 1% significance.

A.2 VAR Granger Causality/Block Exogeneity Wald Tests

VAR Granger Causality/Block Exogeneity Wald Tests

Date: 12/07/13 Time: 16:08

Sample: 1/02/2008 9/30/2013

Included observations: 807

Dependent variable: CERS2

Excluded	Chi-sq	df	Prob.
CO2S2	99.02701	21	0.0000
COAL2	18.42716	21	0.6218
ELECT_B2	24.44686	21	0.2719
ELECT_P2	20.23657	21	0.5063
FTSE_3002	11.59575	21	0.9499
GAS2	5.442039	21	0.9997
All	172.6456	126	0.0037

Dependent variable: CO2S2

Excluded	Chi-sq	df	Prob.
CERS2	63.20821	21	0.0000
COAL2	22.57589	21	0.3670
ELECT_B2	34.64928	21	0.0308
ELECT_P2	33.42373	21	0.0417
FTSE_3002	36.34624	21	0.0200
GAS2	16.32755	21	0.7510
All	182.9404	126	0.0007

Dependent variable: COAL2

Excluded	Chi-sq	df	Prob.
CERS2	9.885429	21	0.9804
CO2S2	36.51699	21	0.0191
ELECT_B2	16.95910	21	0.7136
ELECT_P2	17.02325	21	0.7097
FTSE_3002	34.61127	21	0.0311
GAS2	54.99657	21	0.0001
All	191.3412	126	0.0002

Dependent variable: ELECT_B2

Excluded	Chi-sq	df	Prob.
CERS2	14.79532	21	0.8331
CO2S2	20.61268	21	0.4828
COAL2	15.01395	21	0.8223
ELECT_P2	28.77608	21	0.1195
FTSE_3002	34.88607	21	0.0291
GAS2	47.86061	21	0.0007

All	176.3949	126	0.0021
-----	----------	-----	--------

Dependent variable: ELECT_P2

Excluded	Chi-sq	df	Prob.
CERS2	11.85070	21	0.9436
CO2S2	11.39516	21	0.9545
COAL2	18.01230	21	0.6482
ELECT_B2	18.00957	21	0.6484
FTSE_3002	24.10306	21	0.2881
GAS2	57.88432	21	0.0000
All	151.4116	126	0.0611

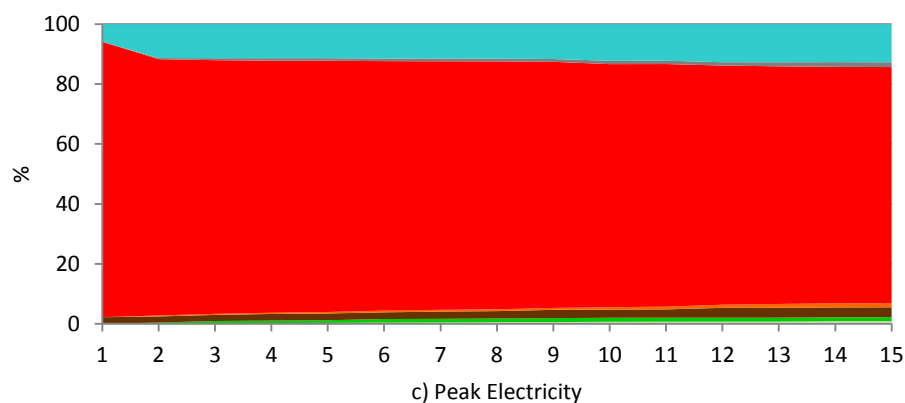
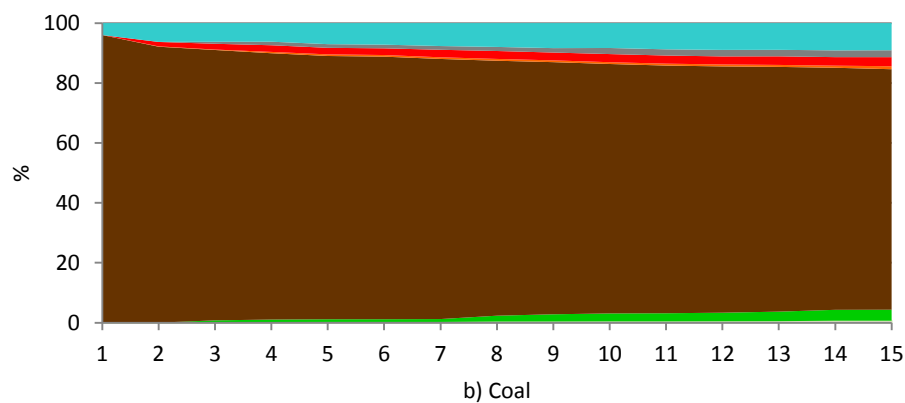
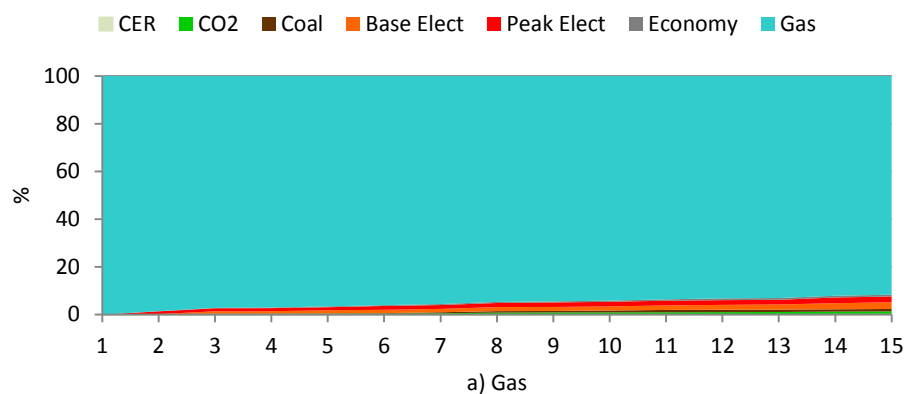
Dependent variable: FTSE_3002

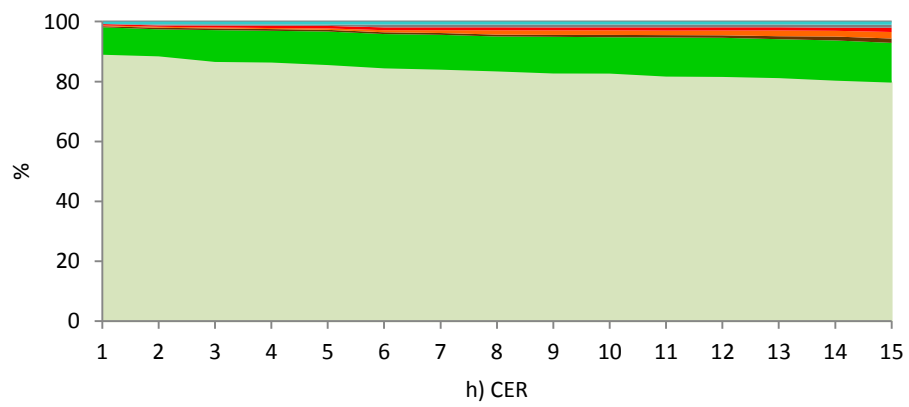
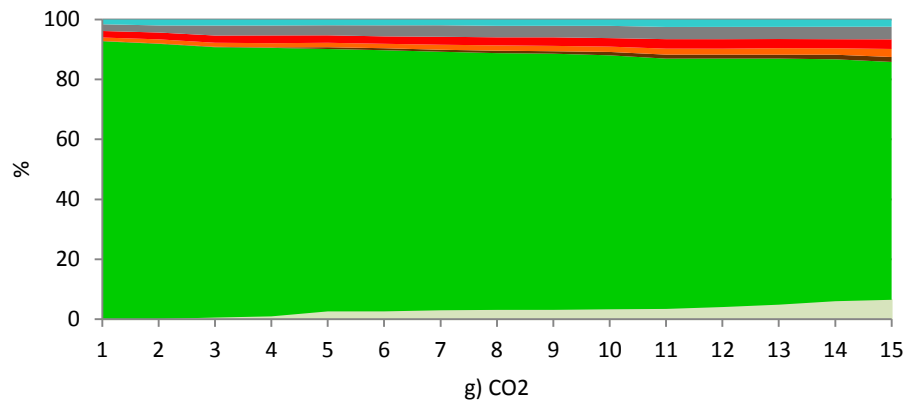
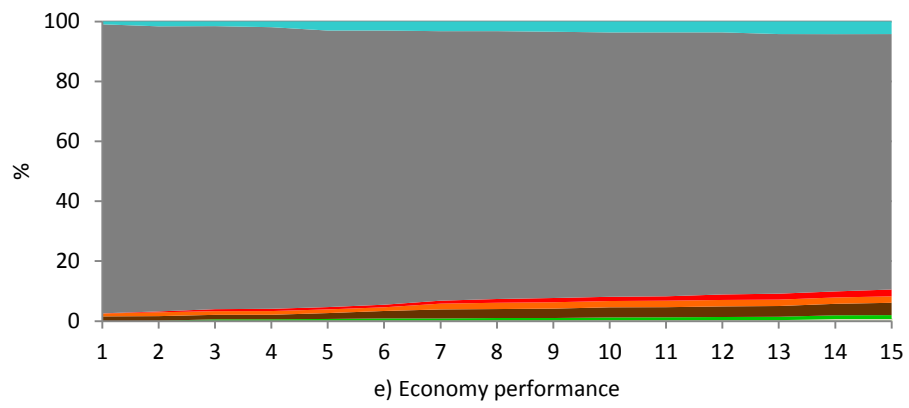
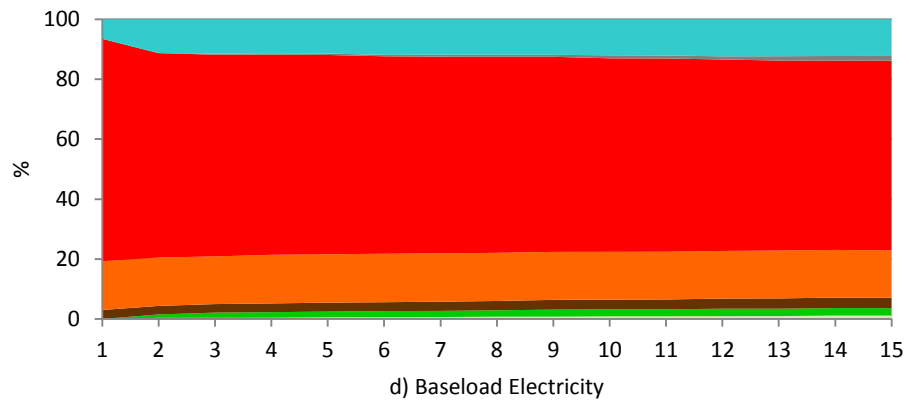
Excluded	Chi-sq	df	Prob.
CERS2	9.323784	21	0.9864
CO2S2	16.25709	21	0.7550
COAL2	38.89758	21	0.0101
ELECT_B2	30.79992	21	0.0771
ELECT_P2	41.34748	21	0.0051
GAS2	44.93163	21	0.0018
All	202.1573	126	0.0000

Dependent variable: GAS2

Excluded	Chi-sq	df	Prob.
CERS2	8.915378	21	0.9899
CO2S2	13.02263	21	0.9078
COAL2	21.51825	21	0.4277
ELECT_B2	35.74538	21	0.0233
ELECT_P2	39.74374	21	0.0080
FTSE_3002	15.51662	21	0.7962
All	145.1583	126	0.1166

A.3 Variance decomposition





A.4 VAR output

Vector Autoregression Estimates
Date: 12/07/13 Time: 16:08
Sample (adjusted): 9/17/2008 9/30/2013
Included observations: 807 after adjustments
Standard errors in () & t-statistics in []

	CERS2	CO2S2	COAL2	ELECT B2	ELECT P2	FTSE 3002	GAS2
CERS2(-1)	-0.108282 (0.04104) [-2.63820]	-0.014941 (0.02383) [-0.62695]	0.005033 (0.01180) [0.42660]	0.022918 (0.01342) [1.70768]	0.017669 (0.01565) [1.12869]	-0.005203 (0.00920) [-0.56588]	0.002303 (0.02273) [0.10132]
CERS2(-2)	0.086973 (0.04163) [2.08915]	0.044040 (0.02417) [1.82199]	-0.009110 (0.01197) [-0.76132]	0.001580 (0.01361) [0.11609]	0.008476 (0.01588) [0.53382]	-0.003234 (0.00933) [-0.34680]	0.002296 (0.02306) [0.09959]
CERS2(-3)	0.006987 (0.04001) [0.17463]	0.037952 (0.02323) [1.63384]	0.007215 (0.01150) [0.62746]	0.001479 (0.01308) [0.11306]	0.008117 (0.01526) [0.53194]	0.001058 (0.00896) [0.11804]	-0.004910 (0.02216) [-0.22159]
CERS2(-4)	-0.089048 (0.04009) [-2.22147]	-0.081262 (0.02327) [-3.49151]	-0.000843 (0.01152) [-0.07312]	0.015773 (0.01311) [1.20339]	0.013783 (0.01529) [0.90154]	0.006919 (0.00898) [0.77043]	0.001681 (0.02220) [0.07573]
CERS2(-5)	0.051606 (0.04119) [1.25280]	-0.006858 (0.02392) [-0.28675]	-0.000324 (0.01184) [-0.02738]	0.003503 (0.01347) [0.26009]	-0.007640 (0.01571) [-0.48627]	0.002891 (0.00923) [0.31324]	-0.003979 (0.02281) [-0.17440]
CERS2(-6)	0.055624 (0.04041) [1.37643]	0.035562 (0.02346) [1.51561]	-0.004245 (0.01162) [-0.36544]	0.005955 (0.01321) [0.45070]	0.007330 (0.01541) [0.47557]	-0.002613 (0.00905) [-0.28864]	0.012357 (0.02238) [0.55211]
CERS2(-7)	-0.029311 (0.04005) [-0.73191]	0.016034 (0.02325) [0.68956]	-0.014890 (0.01151) [-1.29353]	0.011501 (0.01309) [0.87828]	0.012582 (0.01527) [0.82375]	-0.003869 (0.00897) [-0.43120]	0.019411 (0.02218) [0.87517]
CERS2(-8)	0.035476 (0.03939) [0.90067]	0.000277 (0.02287) [0.01210]	0.000244 (0.01132) [0.02154]	0.009775 (0.01288) [0.75893]	-0.000154 (0.01502) [-0.01028]	-0.001551 (0.00882) [-0.17572]	-0.004276 (0.02181) [-0.19600]
CERS2(-9)	-0.098367 (0.03933) [-2.50082]	-0.022698 (0.02284) [-0.99387]	-0.003813 (0.01131) [-0.33723]	0.015137 (0.01286) [1.17691]	0.015387 (0.01500) [1.02563]	-0.004874 (0.00881) [-0.55313]	0.004454 (0.02178) [0.20448]
CERS2(-10)	-0.109344 (0.03938) [-2.77687]	0.021834 (0.02286) [0.95500]	0.003242 (0.01132) [0.28640]	0.007700 (0.01288) [0.59808]	0.010725 (0.01502) [0.71416]	0.000313 (0.00882) [0.03547]	0.010102 (0.02181) [0.46326]
CERS2(-11)	0.117629 (0.03938) [2.98677]	0.052883 (0.02287) [2.31267]	0.001553 (0.01132) [0.13722]	0.005389 (0.01288) [0.41852]	0.004854 (0.01502) [0.32317]	0.003687 (0.00882) [0.41793]	0.017730 (0.02181) [0.81286]
CERS2(-12)	0.013135 (0.03903) [0.33651]	0.080274 (0.02266) [3.54208]	-0.000472 (0.01122) [-0.04208]	0.001865 (0.01276) [0.14616]	0.003014 (0.01489) [0.20243]	0.001011 (0.00874) [0.11558]	0.002393 (0.02162) [0.11071]
CERS2(-13)	-0.063460 (0.03928) [-1.61557]	0.078233 (0.02281) [3.43028]	0.014126 (0.01129) [1.25110]	0.017471 (0.01284) [1.36032]	0.012688 (0.01498) [0.84690]	0.013720 (0.00880) [1.55913]	0.014302 (0.02175) [0.65746]
CERS2(-14)	0.075441 (0.03970) [1.90034]	-0.039629 (0.02305) [-1.71928]	0.004711 (0.01141) [0.41286]	0.000695 (0.01298) [0.05357]	-0.004129 (0.01514) [-0.27268]	0.002650 (0.00889) [0.29799]	0.022785 (0.02199) [1.03636]
CERS2(-15)	0.093429 (0.03961) [2.35856]	0.012707 (0.02300) [0.55248]	0.007090 (0.01139) [0.62272]	-0.006606 (0.01295) [-0.50999]	0.002411 (0.01511) [0.15960]	0.012502 (0.00887) [1.40883]	0.016009 (0.02194) [0.72974]
CERS2(-16)	0.096956 (0.03966) [2.44450]	0.017077 (0.02303) [0.74154]	-0.016903 (0.01140) [-1.48267]	-0.010621 (0.01297) [-0.81898]	-0.010876 (0.01513) [-0.71898]	-0.006986 (0.00889) [-0.78626]	0.007275 (0.02197) [0.33117]
CERS2(-17)	0.101727 (0.03887) [2.61687]	-0.003741 (0.02257) [-0.16574]	-0.004962 (0.01117) [-0.44411]	-0.003907 (0.01271) [-0.30735]	-0.010491 (0.01483) [-0.70756]	0.000995 (0.00871) [0.11425]	0.004479 (0.02153) [0.20804]
CERS2(-18)	-0.079401 (0.03902) [-2.03478]	0.073771 (0.02266) [3.25604]	-0.003727 (0.01122) [-0.33232]	0.022283 (0.01276) [1.74646]	0.016097 (0.01488) [1.08159]	-0.003078 (0.00874) [-0.35212]	0.036459 (0.02161) [1.68706]
CERS2(-19)	-0.168452 (0.03954) [-4.26007]	-0.016946 (0.02296) [-0.73809]	0.002503 (0.01137) [0.22018]	0.007676 (0.01293) [0.59369]	0.005771 (0.01508) [0.38266]	-0.004183 (0.00886) [-0.47224]	0.015716 (0.02190) [0.71763]
CERS2(-20)	0.074949 (0.03978) [1.88430]	0.018686 (0.02309) [0.80912]	0.007067 (0.01143) [0.61814]	0.002812 (0.01301) [0.21625]	0.007132 (0.01517) [0.47011]	0.004654 (0.00891) [0.52233]	0.007668 (0.02203) [0.34809]
CERS2(-21)	-0.085776 (0.03825)	0.001207 (0.02221)	0.009075 (0.01100)	-0.017188 (0.01251)	-0.020669 (0.01459)	0.004132 (0.00857)	-0.019256 (0.02118)

	[-2.24239]	[0.05433]	[0.82539]	[-1.37425]	[-1.41669]	[0.48221]	[-0.90896]
CO2S2(-1)	0.062368 (0.07468) [0.83517]	0.084257 (0.04336) [1.94326]	-0.000869 (0.02146) [-0.04047]	0.052092 (0.02442) [2.13338]	0.024706 (0.02848) [0.86743]	0.012256 (0.01673) [0.73259]	-0.040031 (0.04136) [-0.96792]
CO2S2(-2)	-0.297643 (0.07367) [-4.04040]	-0.195483 (0.04277) [-4.57034]	-0.036649 (0.02117) [-1.73083]	-0.037770 (0.02409) [-1.56806]	-0.045530 (0.02810) [-1.62048]	-0.022960 (0.01650) [-1.39124]	-0.048101 (0.04080) [-1.17899]
CO2S2(-3)	0.015673 (0.07396) [0.21192]	-0.045555 (0.04294) [-1.06085]	-0.015123 (0.02126) [-0.71137]	0.005886 (0.02418) [0.24339]	0.000635 (0.02821) [0.02253]	0.004945 (0.01657) [0.29848]	0.013819 (0.04096) [0.33737]
CO2S2(-4)	0.186426 (0.07165) [2.60195]	0.154347 (0.04160) [3.71021]	0.011172 (0.02059) [0.54249]	0.014134 (0.02343) [0.60332]	0.015847 (0.02733) [0.57989]	-0.022204 (0.01605) [-1.38334]	-0.035737 (0.03968) [-0.90062]
CO2S2(-5)	-0.190032 (0.07243) [-2.62370]	-0.070114 (0.04205) [-1.66726]	0.000985 (0.02082) [0.04732]	-0.038867 (0.02368) [-1.64115]	-0.043218 (0.02762) [-1.56446]	0.017639 (0.01623) [1.08709]	-0.006546 (0.04011) [-0.16318]
CO2S2(-6)	-0.072254 (0.07102) [-1.01740]	-0.059833 (0.04123) [-1.45103]	0.024071 (0.02041) [1.17921]	0.009013 (0.02322) [0.38815]	0.011925 (0.02709) [0.44026]	0.001292 (0.01591) [0.08124]	-0.036076 (0.03933) [-0.91722]
CO2S2(-7)	0.064766 (0.07111) [0.91078]	-0.020319 (0.04129) [-0.49214]	-0.041452 (0.02044) [-2.02800]	-0.030680 (0.02325) [-1.31950]	-0.028326 (0.02712) [-1.04441]	-0.002794 (0.01593) [-0.17538]	0.034152 (0.03938) [0.86719]
CO2S2(-8)	0.112685 (0.07050) [1.59847]	0.025090 (0.04093) [0.61300]	-0.043964 (0.02026) [-2.16970]	0.010529 (0.02305) [0.45678]	0.011679 (0.02689) [0.43436]	0.000651 (0.01579) [0.04121]	0.007955 (0.03904) [0.20375]
CO2S2(-9)	0.011813 (0.07212) [0.16379]	0.015660 (0.04187) [0.37399]	-0.038916 (0.02073) [-1.87732]	0.000232 (0.02358) [0.00984]	-0.008838 (0.02751) [-0.32132]	-0.017410 (0.01616) [-1.07755]	0.018439 (0.03994) [0.46165]
CO2S2(-10)	0.299859 (0.07145) [4.19669]	0.020410 (0.04149) [0.49197]	0.008026 (0.02054) [0.39078]	-0.000575 (0.02336) [-0.02462]	-0.013162 (0.02725) [-0.48296]	0.001206 (0.01601) [0.07533]	0.003211 (0.03957) [0.08115]
CO2S2(-11)	0.036285 (0.07895) [0.45961]	-0.014729 (0.04584) [-0.32131]	-0.008412 (0.02269) [-0.37070]	-0.030015 (0.02581) [-1.16272]	-0.000466 (0.03011) [-0.01547]	0.008247 (0.01769) [0.46629]	0.031601 (0.04372) [0.72274]
CO2S2(-12)	-0.024422 (0.08118) [-0.30083]	-0.198249 (0.04714) [-4.20590]	0.046914 (0.02333) [2.01045]	-0.021217 (0.02654) [-0.79928]	-0.028001 (0.03096) [-0.90433]	-0.008757 (0.01819) [-0.48149]	-0.025299 (0.04496) [-0.56270]
CO2S2(-13)	0.266153 (0.08236) [3.23156]	-0.020045 (0.04782) [-0.41918]	0.028090 (0.02367) [1.18658]	0.000490 (0.02693) [0.01818]	-0.000915 (0.03141) [-0.02914]	0.011871 (0.01845) [0.64338]	0.005512 (0.04561) [0.12085]
CO2S2(-14)	-0.112990 (0.08428) [-1.34062]	-0.037986 (0.04894) [-0.77624]	-0.000158 (0.02423) [-0.00650]	-0.040293 (0.02756) [-1.46210]	-0.044553 (0.03215) [-1.38599]	-0.005249 (0.01888) [-0.27800]	0.008133 (0.04668) [0.17424]
CO2S2(-15)	-0.190485 (0.08278) [-2.30101]	0.005950 (0.04807) [0.12379]	0.001700 (0.02379) [0.07144]	0.046833 (0.02707) [1.73020]	0.022911 (0.03157) [0.72565]	-0.013967 (0.01855) [-0.75310]	-0.046954 (0.04585) [-1.02415]
CO2S2(-16)	-0.011381 (0.08350) [-0.13629]	-0.176945 (0.04848) [-3.64953]	0.031312 (0.02400) [1.30454]	0.022687 (0.02730) [0.83090]	0.030482 (0.03185) [0.95707]	0.029079 (0.01871) [1.55444]	0.033443 (0.04625) [0.72314]
CO2S2(-17)	-0.003701 (0.08294) [-0.04462]	-0.094481 (0.04816) [-1.96184]	0.006731 (0.02384) [0.28233]	-0.010433 (0.02712) [-0.38468]	-0.006404 (0.03164) [-0.20243]	0.014947 (0.01858) [0.80439]	0.056476 (0.04594) [1.22944]
CO2S2(-18)	0.245217 (0.08292) [2.95731]	-0.088393 (0.04814) [-1.83600]	0.044440 (0.02383) [1.86457]	-0.004664 (0.02711) [-0.17201]	-0.008207 (0.03163) [-0.25951]	0.013446 (0.01858) [0.72384]	-0.062201 (0.04592) [-1.35447]
CO2S2(-19)	-0.115144 (0.08323) [-1.38339]	0.106890 (0.04833) [2.21182]	0.007870 (0.02392) [0.32897]	-0.031239 (0.02722) [-1.14783]	-0.031893 (0.03175) [-1.00465]	0.005949 (0.01865) [0.31905]	0.013857 (0.04610) [0.30061]
CO2S2(-20)	-0.152271 (0.08457) [-1.80051]	-0.110836 (0.04910) [-2.25718]	0.009129 (0.02431) [0.37556]	-0.024618 (0.02765) [-0.89026]	-0.030123 (0.03226) [-0.93389]	-0.010781 (0.01895) [-0.56901]	0.011351 (0.04684) [0.24235]
CO2S2(-21)	0.056631 (0.08021) [0.70600]	-0.010020 (0.04657) [-0.21515]	-0.050090 (0.02306) [-2.17252]	-0.025091 (0.02623) [-0.95663]	-0.007033 (0.03059) [-0.22988]	0.035021 (0.01797) [1.94885]	-0.038822 (0.04442) [-0.87389]
COAL2(-1)	0.210650 (0.13728) [1.53450]	-0.000470 (0.07970) [-0.00589]	-0.037482 (0.03946) [-0.94991]	0.035174 (0.04489) [0.78364]	-0.019409 (0.05236) [-0.37070]	0.001429 (0.03075) [0.04647]	0.010010 (0.07603) [0.13167]
COAL2(-2)	-0.029185 (0.13805) [-0.21141]	0.013011 (0.08015) [0.16232]	-0.062605 (0.03968) [-1.57770]	0.045719 (0.04514) [1.01283]	0.022890 (0.05265) [0.43474]	0.035413 (0.03093) [1.14505]	-0.000624 (0.07646) [-0.00816]
COAL2(-3)	0.025106 (0.14986) [0.16753]	-0.012679 (0.08701) [-0.14571]	0.064637 (0.04308) [1.50054]	-0.003750 (0.04900) [-0.07652]	-0.041601 (0.05716) [-0.72783]	-0.009095 (0.03357) [-0.27092]	0.020614 (0.08300) [0.24837]

COAL2(-4)	0.008542 (0.13182) [0.06480]	0.185485 (0.07654) [2.42345]	-0.036790 (0.03789) [-0.97096]	-0.018879 (0.04310) [-0.43800]	-0.024055 (0.05028) [-0.47845]	0.069765 (0.02953) [2.36239]	0.052483 (0.07301) [0.71889]
COAL2(-5)	0.140550 (0.13005) [1.08076]	-0.034782 (0.07551) [-0.46064]	-0.001688 (0.03738) [-0.04515]	-0.020956 (0.04252) [-0.49283]	-0.013236 (0.04960) [-0.26686]	0.051301 (0.02913) [1.76085]	-0.045991 (0.07202) [-0.63856]
COAL2(-6)	0.124945 (0.12721) [0.98216]	0.059570 (0.07386) [0.80649]	-0.037753 (0.03657) [-1.03246]	-0.047717 (0.04160) [-1.14713]	-0.070181 (0.04852) [-1.44645]	-0.039949 (0.02850) [-1.40174]	-0.087008 (0.07045) [-1.23496]
COAL2(-7)	-0.046014 (0.12863) [-0.35772]	0.054808 (0.07469) [0.73385]	-0.007843 (0.03697) [-0.21211]	-0.032414 (0.04206) [-0.77068]	-0.040392 (0.04906) [-0.82332]	-0.001476 (0.02882) [-0.05122]	0.057028 (0.07124) [0.80053]
COAL2(-8)	-0.019772 (0.12818) [-0.15425]	-0.061808 (0.07442) [-0.83049]	0.043311 (0.03684) [1.17553]	0.040990 (0.04191) [0.97800]	0.063085 (0.04889) [1.29041]	0.034621 (0.02872) [1.20564]	0.018814 (0.07099) [0.26502]
COAL2(-9)	0.237825 (0.13100) [1.81546]	-0.063851 (0.07606) [-0.83948]	0.051318 (0.03765) [1.36289]	-0.016222 (0.04283) [-0.37873]	-0.024504 (0.04996) [-0.49043]	0.063252 (0.02935) [2.15527]	0.066909 (0.07255) [0.92224]
COAL2(-10)	0.081822 (0.12573) [0.65079]	0.178458 (0.07300) [2.44466]	0.043421 (0.03614) [1.20152]	-0.010621 (0.04111) [-0.25835]	-0.018624 (0.04795) [-0.38838]	0.028325 (0.02817) [1.00564]	-0.110542 (0.06963) [-1.58755]
COAL2(-11)	-0.005226 (0.12742) [-0.04101]	-0.045628 (0.07398) [-0.61674]	0.036198 (0.03663) [0.98833]	-0.071729 (0.04166) [-1.72160]	-0.115075 (0.04860) [-2.36785]	-0.039460 (0.02855) [-1.38233]	0.050594 (0.07057) [0.71695]
COAL2(-12)	-0.058909 (0.12914) [-0.45615]	0.041546 (0.07498) [0.55407]	-0.011322 (0.03712) [-0.30500]	-0.007757 (0.04223) [-0.18371]	0.010814 (0.04926) [0.21955]	-0.009475 (0.02893) [-0.32751]	0.012854 (0.07152) [0.17972]
COAL2(-13)	0.256524 (0.12962) [1.97904]	0.114373 (0.07526) [1.51971]	0.018085 (0.03726) [0.48541]	0.007836 (0.04238) [0.18488]	0.005311 (0.04944) [0.10742]	0.029015 (0.02904) [0.99921]	0.000822 (0.07179) [0.01146]
COAL2(-14)	0.083892 (0.12715) [0.65981]	0.060744 (0.07382) [0.82283]	-0.034061 (0.03655) [-0.93199]	-0.030518 (0.04157) [-0.73406]	0.005711 (0.04849) [0.11777]	0.058409 (0.02848) [2.05059]	0.072612 (0.07042) [1.03119]
COAL2(-15)	0.157303 (0.12848) [1.22431]	-0.111088 (0.07460) [-1.48912]	-0.003681 (0.03693) [-0.09966]	0.000937 (0.04201) [0.02230]	-0.016965 (0.04900) [-0.34620]	-0.040690 (0.02878) [-1.41366]	0.003385 (0.07116) [0.04757]
COAL2(-16)	-0.134397 (0.12689) [-1.05916]	0.023037 (0.07367) [0.31269]	0.009803 (0.03647) [0.26876]	0.037009 (0.04149) [0.89200]	0.020675 (0.04840) [0.42720]	0.029204 (0.02843) [1.02733]	-0.003496 (0.07027) [-0.04975]
COAL2(-17)	0.162927 (0.13020) [1.25140]	0.036892 (0.07559) [0.48804]	-0.018829 (0.03742) [-0.50315]	0.074827 (0.04257) [1.75770]	0.074414 (0.04966) [1.49856]	-0.048944 (0.02917) [-1.67804]	0.153849 (0.07211) [2.13367]
COAL2(-18)	-0.096931 (0.13166) [-0.73619]	-0.028067 (0.07645) [-0.36715]	-0.062757 (0.03785) [-1.65825]	-0.016960 (0.04305) [-0.39395]	0.005941 (0.05022) [0.11832]	-0.026804 (0.02950) [-0.90872]	0.051878 (0.07292) [0.71144]
COAL2(-19)	-0.016866 (0.13002) [-0.12971]	-0.088799 (0.07549) [-1.17624]	-0.019775 (0.03737) [-0.52911]	1.85E-05 (0.04251) [0.00043]	0.025366 (0.04959) [0.51151]	0.050816 (0.02913) [1.74451]	0.068883 (0.07201) [0.95657]
COAL2(-20)	-0.189115 (0.12862) [-1.47029]	-0.019382 (0.07468) [-0.25953]	-0.020628 (0.03697) [-0.55793]	-0.028823 (0.04206) [-0.68532]	-0.052891 (0.04906) [-1.07815]	0.010355 (0.02882) [0.35936]	0.095243 (0.07123) [1.33703]
COAL2(-21)	0.022177 (0.13173) [0.16836]	-0.089743 (0.07648) [-1.17335]	0.048350 (0.03786) [1.27694]	0.023929 (0.04307) [0.55556]	0.013122 (0.05024) [0.26118]	-0.028585 (0.02951) [-0.96863]	-0.139898 (0.07295) [-1.91762]
ELECT_B2(-1)	-0.133876 (0.29325) [-0.45652]	-0.234779 (0.17027) [-1.37889]	-0.079504 (0.08429) [-0.94321]	-0.329161 (0.09589) [-3.43282]	-0.207196 (0.11185) [-1.85251]	-0.108007 (0.06570) [-1.64403]	-0.047399 (0.16241) [-0.29185]
ELECT_B2(-2)	0.059337 (0.29309) [0.20246]	-0.009092 (0.17017) [-0.05343]	0.001709 (0.08424) [0.02029]	-0.082066 (0.09583) [-0.85635]	-0.025715 (0.11178) [-0.23005]	-0.003232 (0.06566) [-0.04922]	-0.394800 (0.16232) [-2.43227]
ELECT_B2(-3)	-0.226324 (0.28641) [-0.79021]	-0.229487 (0.16629) [-1.38001]	-0.122396 (0.08232) [-1.48675]	-0.153830 (0.09365) [-1.64262]	-0.018873 (0.10924) [-0.17277]	-0.050128 (0.06416) [-0.78125]	-0.137267 (0.15862) [-0.86539]
ELECT_B2(-4)	0.193694 (0.25247) [0.76719]	0.083955 (0.14659) [0.57272]	0.037926 (0.07257) [0.52262]	0.000749 (0.08255) [0.00907]	0.059868 (0.09629) [0.62173]	0.016520 (0.05656) [0.29207]	-0.332656 (0.13982) [-2.37909]
ELECT_B2(-5)	-0.285561 (0.25534) [-1.11837]	-0.047146 (0.14825) [-0.31801]	-0.028429 (0.07339) [-0.38736]	-0.105109 (0.08349) [-1.25895]	-0.015580 (0.09739) [-0.15998]	-0.001960 (0.05720) [-0.03427]	-0.007036 (0.14141) [-0.04976]
ELECT_B2(-6)	-0.515805 (0.24792) [-2.08052]	-0.233548 (0.14395) [-1.62245]	-0.008988 (0.07126) [-0.12613]	-0.017873 (0.08106) [-0.22048]	0.001078 (0.09456) [0.01140]	-0.134374 (0.05554) [-2.41936]	-0.137224 (0.13730) [-0.99942]
ELECT_B2(-7)	0.412585 (0.24575)	0.122739 (0.14269)	-0.029417 (0.07064)	0.068616 (0.08036)	0.108548 (0.09373)	-0.103620 (0.05506)	0.062445 (0.13610)

	[1.67887]	[0.86019]	[-0.41644]	[0.85391]	[1.15809]	[-1.88210]	[0.45881]
ELECT B2(-8)	0.149297 (0.25559) [0.58412]	-0.014812 (0.14840) [-0.09981]	-0.037538 (0.07347) [-0.51096]	-0.137059 (0.08357) [-1.63999]	-0.088928 (0.09748) [-0.91224]	-0.030730 (0.05726) [-0.53668]	-0.003560 (0.14155) [-0.02515]
ELECT B2(-9)	-0.107298 (0.25442) [-0.42173]	-0.022223 (0.14772) [-0.15044]	0.044000 (0.07313) [0.60167]	0.039173 (0.08319) [0.47089]	0.125676 (0.09704) [1.29513]	-0.036088 (0.05700) [-0.63315]	0.101911 (0.14091) [0.72326]
ELECT B2(-10)	-0.132639 (0.24981) [-0.53097]	-0.319327 (0.14504) [-2.20161]	-0.050027 (0.07180) [-0.69672]	-0.111865 (0.08168) [-1.36954]	-0.153326 (0.09528) [-1.60927]	-0.066858 (0.05596) [-1.19467]	-0.113003 (0.13835) [-0.81680]
ELECT B2(-11)	-0.307424 (0.25615) [-1.20017]	-0.035468 (0.14873) [-0.23848]	0.037551 (0.07363) [0.51002]	-0.089365 (0.08376) [-1.06697]	-0.130406 (0.09770) [-1.33481]	-0.052821 (0.05738) [-0.92047]	0.168237 (0.14186) [1.18592]
ELECT_B2(-12)	-0.638892 (0.25948) [-2.46215]	-0.338788 (0.15066) [-2.24867]	0.020975 (0.07459) [0.28122]	0.121638 (0.08485) [1.43364]	0.131516 (0.09897) [1.32887]	-0.016710 (0.05813) [-0.28744]	0.186470 (0.14371) [1.29756]
ELECT B2(-13)	-0.052500 (0.25476) [-0.20608]	-0.095346 (0.14792) [-0.64458]	-0.079960 (0.07323) [-1.09193]	0.017244 (0.08330) [0.20701]	0.049577 (0.09717) [0.51022]	-0.055046 (0.05707) [-0.96447]	-0.346843 (0.14109) [-2.45826]
ELECT B2(-14)	-0.424773 (0.26361) [-1.61135]	-0.442059 (0.15306) [-2.88817]	-0.112215 (0.07577) [-1.48096]	-0.038185 (0.08620) [-0.44300]	-0.016903 (0.10054) [-0.16812]	0.005238 (0.05906) [0.08870]	-0.310062 (0.14599) [-2.12379]
ELECT B2(-15)	-0.517949 (0.25795) [-2.00792]	-0.141108 (0.14977) [-0.94215]	-0.070026 (0.07415) [-0.94444]	0.006573 (0.08434) [0.07793]	-0.003742 (0.09838) [-0.03803]	-0.032424 (0.05779) [-0.56108]	-0.268966 (0.14286) [-1.88272]
ELECT B2(-16)	-0.002259 (0.25178) [-0.00897]	0.086550 (0.14619) [0.59204]	0.123726 (0.07237) [1.70961]	0.090306 (0.08233) [1.09693]	0.072914 (0.09603) [0.75929]	-0.048800 (0.05641) [-0.86517]	-0.044260 (0.13944) [-0.31741]
ELECT B2(-17)	-0.111246 (0.24860) [-0.44750]	0.096430 (0.14434) [0.66808]	0.015911 (0.07146) [0.22267]	0.031764 (0.08128) [0.39077]	0.066594 (0.09481) [0.70236]	0.165963 (0.05569) [2.98001]	-0.163911 (0.13768) [-1.19054]
ELECT B2(-18)	-0.032090 (0.25598) [-0.12536]	0.358731 (0.14862) [2.41366]	-0.093456 (0.07358) [-1.27018]	0.106046 (0.08370) [1.26699]	0.132234 (0.09763) [1.35445]	-0.021802 (0.05735) [-0.38019]	-0.117304 (0.14177) [-0.82745]
ELECT B2(-19)	0.125164 (0.24564) [0.50955]	-0.044934 (0.14262) [-0.31506]	-0.048061 (0.07061) [-0.68069]	0.022686 (0.08032) [0.28246]	0.045220 (0.09369) [0.48267]	0.093423 (0.05503) [1.69768]	0.042787 (0.13604) [0.31452]
ELECT B2(-20)	-0.125220 (0.25597) [-0.48920]	0.176938 (0.14862) [1.19054]	-0.052014 (0.07357) [-0.70696]	-0.008961 (0.08370) [-0.10707]	-0.003250 (0.09763) [-0.03329]	-0.066782 (0.05734) [-1.16458]	0.036796 (0.14176) [0.25956]
ELECT_B2(-21)	-0.285773 (0.25115) [-1.13787]	0.148825 (0.14582) [1.02060]	0.040676 (0.07219) [0.56346]	0.102435 (0.08212) [1.24739]	0.030093 (0.09579) [0.31416]	0.058027 (0.05626) [1.03133]	-0.182227 (0.13909) [-1.31013]
ELECT P2(-1)	0.086778 (0.25490) [0.34045]	0.225533 (0.14800) [1.52390]	0.157514 (0.07327) [2.14988]	0.292778 (0.08335) [3.51283]	0.198714 (0.09722) [2.04400]	0.050775 (0.05710) [0.88916]	0.210717 (0.14117) [1.49268]
ELECT P2(-2)	-0.141588 (0.25766) [-0.54951]	-0.026404 (0.14960) [-0.17649]	0.057234 (0.07406) [0.77279]	-0.004822 (0.08425) [-0.05724]	-0.028886 (0.09827) [-0.29393]	-0.019200 (0.05772) [-0.33263]	0.362684 (0.14270) [2.54159]
ELECT P2(-3)	0.260843 (0.25253) [1.03292]	0.260702 (0.14662) [1.77804]	0.055808 (0.07259) [0.76885]	0.053358 (0.08257) [0.64620]	-0.052697 (0.09632) [-0.54713]	0.047613 (0.05657) [0.84161]	0.146034 (0.13986) [1.04417]
ELECT P2(-4)	-0.082191 (0.23175) [-0.35465]	-0.078987 (0.13456) [-0.58700]	-0.025371 (0.06661) [-0.38086]	-0.065028 (0.07578) [-0.85813]	-0.103559 (0.08839) [-1.17160]	-0.006964 (0.05192) [-0.13413]	0.289046 (0.12835) [2.25201]
ELECT P2(-5)	0.174549 (0.23640) [0.73837]	0.035559 (0.13726) [0.25907]	0.015205 (0.06795) [0.22377]	0.094503 (0.07730) [1.22260]	0.002776 (0.09016) [0.03079]	0.005990 (0.05296) [0.11310]	0.141165 (0.13092) [1.07824]
ELECT P2(-6)	0.459964 (0.23062) [1.99449]	0.280879 (0.13390) [2.09768]	0.050992 (0.06629) [0.76926]	0.016799 (0.07541) [0.22279]	-0.018585 (0.08796) [-0.21130]	0.122220 (0.05166) [2.36565]	0.146393 (0.12772) [1.14620]
ELECT P2(-7)	-0.411855 (0.23248) [-1.77154]	-0.051741 (0.13498) [-0.38331]	0.059048 (0.06682) [0.88362]	-0.025085 (0.07602) [-0.33000]	-0.047823 (0.08867) [-0.53934]	0.120417 (0.05208) [2.31203]	0.044948 (0.12875) [0.34910]
ELECT P2(-8)	-0.080635 (0.23663) [-0.34077]	0.111816 (0.13739) [0.81386]	0.051905 (0.06802) [0.76314]	0.135215 (0.07737) [1.74761]	0.101088 (0.09025) [1.12009]	0.064424 (0.05301) [1.21529]	0.067160 (0.13105) [0.51248]
ELECT P2(-9)	0.143939 (0.23882) [0.60271]	0.048992 (0.13866) [0.35332]	-0.005836 (0.06865) [-0.08502]	-0.047119 (0.07809) [-0.60340]	-0.107526 (0.09109) [-1.18049]	0.022867 (0.05350) [0.42739]	-0.015460 (0.13226) [-0.11689]
ELECT P2(-10)	-0.043627 (0.23366) [-0.18671]	0.173947 (0.13567) [1.28216]	0.049413 (0.06716) [0.73572]	0.120366 (0.07640) [1.57545]	0.165521 (0.08912) [1.85733]	0.077416 (0.05235) [1.47893]	0.149831 (0.12941) [1.15784]

ELECT_P2(-11)	0.172821 (0.23988) [0.72045]	0.041026 (0.13928) [0.29456]	-0.038651 (0.06895) [-0.56057]	0.125797 (0.07843) [1.60384]	0.162387 (0.09149) [1.77491]	0.078000 (0.05374) [1.45145]	-0.104446 (0.13285) [-0.78619]
ELECT_P2(-12)	0.508683 (0.24320) [2.09163]	0.290146 (0.14121) [2.05478]	-0.010765 (0.06990) [-0.15400]	-0.082632 (0.07952) [-1.03912]	-0.090776 (0.09276) [-0.97865]	0.006021 (0.05448) [0.11051]	-0.121526 (0.13469) [-0.90227]
ELECT_P2(-13)	0.066252 (0.23710) [0.27942]	0.125234 (0.13767) [0.90969]	0.053160 (0.06815) [0.78001]	0.050292 (0.07753) [0.64870]	0.026811 (0.09043) [0.29648]	0.077310 (0.05312) [1.45545]	0.387592 (0.13131) [2.95166]
ELECT_P2(-14)	0.470494 (0.24867) [1.89207]	0.437812 (0.14438) [3.03236]	0.106225 (0.07148) [1.48617]	0.111736 (0.08131) [1.37423]	0.085880 (0.09484) [0.90551]	0.031092 (0.05571) [0.55812]	0.278624 (0.13772) [2.02317]
ELECT_P2(-15)	0.374153 (0.24453) [1.53008]	0.098761 (0.14198) [0.69560]	0.049916 (0.07029) [0.71017]	0.042026 (0.07996) [0.52561]	0.055700 (0.09326) [0.59723]	-0.012405 (0.05478) [-0.22644]	0.192854 (0.13543) [1.42404]
ELECT_P2(-16)	0.012420 (0.23914) [0.05194]	0.005669 (0.13885) [0.04083]	-0.121148 (0.06874) [-1.76251]	-0.068002 (0.07819) [-0.86968]	-0.044253 (0.09121) [-0.48519]	0.079049 (0.05357) [1.47553]	0.068841 (0.13244) [0.51979]
ELECT_P2(-17)	-0.003321 (0.23722) [-0.01400]	-0.099680 (0.13773) [-0.72372]	-0.040139 (0.06819) [-0.58868]	-0.029441 (0.07756) [-0.37956]	-0.074184 (0.09048) [-0.81993]	-0.173944 (0.05314) [-3.27311]	0.156395 (0.13138) [1.19043]
ELECT_P2(-18)	0.070543 (0.23932) [0.29477]	-0.268759 (0.13895) [-1.93418]	0.082306 (0.06879) [1.19650]	-0.054828 (0.07825) [-0.70066]	-0.097303 (0.09128) [-1.06603]	0.067171 (0.05361) [1.25287]	0.145671 (0.13254) [1.09907]
ELECT_P2(-19)	-0.148148 (0.23155) [-0.63981]	0.046370 (0.13444) [0.34491]	0.022239 (0.06656) [0.33413]	-0.020589 (0.07571) [-0.27194]	-0.057045 (0.08831) [-0.64594]	-0.110607 (0.05187) [-2.13224]	0.068344 (0.12824) [0.53295]
ELECT_P2(-20)	0.098346 (0.24103) [0.40803]	-0.107100 (0.13994) [-0.76530]	0.055918 (0.06928) [0.80714]	0.057815 (0.07881) [0.73360]	0.064516 (0.09193) [0.70182]	0.039337 (0.05400) [0.72851]	-0.091434 (0.13349) [-0.68497]
ELECT_P2(-21)	0.154846 (0.23751) [0.65194]	-0.126854 (0.13791) [-0.91986]	-0.047480 (0.06827) [-0.69548]	-0.074279 (0.07766) [-0.95644]	0.001574 (0.09059) [0.01737]	-0.077082 (0.05321) [-1.44863]	0.360293 (0.13154) [2.73902]
FTSE_3002(-1)	-0.273955 (0.17774) [-1.54132]	-0.133809 (0.10320) [-1.29660]	0.020731 (0.05109) [0.40578]	0.012341 (0.05812) [0.21235]	0.095735 (0.06779) [1.41223]	0.030992 (0.03982) [0.77832]	-0.053600 (0.09844) [-0.54452]
FTSE_3002(-2)	-0.044258 (0.17230) [-0.25687]	-0.221201 (0.10004) [-2.21115]	-0.100654 (0.04952) [-2.03241]	0.099637 (0.05634) [1.76858]	0.120257 (0.06571) [1.83000]	-0.180922 (0.03860) [-4.68717]	0.068831 (0.09542) [0.72133]
FTSE_3002(-3)	-0.071020 (0.17497) [-0.40589]	0.039522 (0.10159) [0.38903]	0.082535 (0.05029) [1.64107]	-0.039330 (0.05721) [-0.68744]	-0.072335 (0.06673) [-1.08391]	-0.025926 (0.03920) [-0.66139]	0.000971 (0.09690) [0.01002]
FTSE_3002(-4)	-0.104259 (0.17357) [-0.60068]	-0.267608 (0.10078) [-2.65547]	-0.015811 (0.04989) [-0.31692]	-0.023228 (0.05675) [-0.40928]	0.019885 (0.06620) [0.30038]	-0.085161 (0.03888) [-2.19013]	0.095338 (0.09613) [0.99181]
FTSE_3002(-5)	-0.275688 (0.17574) [-1.56873]	-0.144794 (0.10204) [-1.41903]	0.038404 (0.05051) [0.76027]	-0.002426 (0.05746) [-0.04221]	-0.004741 (0.06703) [-0.07073]	-0.065781 (0.03937) [-1.67082]	0.004516 (0.09733) [0.04640]
FTSE_3002(-6)	-0.015747 (0.17325) [-0.09089]	-0.121100 (0.10059) [-1.20389]	-0.039735 (0.04980) [-0.79793]	0.061035 (0.05665) [1.07744]	0.055933 (0.06608) [0.84648]	-0.020025 (0.03881) [-0.51595]	-0.063594 (0.09595) [-0.66280]
FTSE_3002(-7)	-0.141765 (0.17508) [-0.80971]	-0.079087 (0.10165) [-0.77799]	0.070599 (0.05032) [1.40287]	0.017355 (0.05725) [0.30316]	0.018415 (0.06678) [0.27577]	0.008485 (0.03922) [0.21632]	-0.008068 (0.09696) [-0.08321]
FTSE_3002(-8)	-0.139604 (0.17384) [-0.80308]	-0.078790 (0.10093) [-0.78062]	0.039764 (0.04997) [0.79580]	0.006935 (0.05684) [0.12200]	0.014982 (0.06630) [0.22597]	-0.059090 (0.03894) [-1.51730]	-0.068392 (0.09627) [-0.71038]
FTSE_3002(-9)	0.018602 (0.17174) [0.10831]	0.104485 (0.09971) [1.04784]	0.125463 (0.04936) [2.54159]	0.091070 (0.05615) [1.62178]	0.081369 (0.06550) [1.24226]	-0.038455 (0.03847) [-0.99951]	-0.050217 (0.09511) [-0.52797]
FTSE_3002(-10)	-0.238335 (0.16946) [-1.40643]	-0.037076 (0.09839) [-0.37682]	0.012874 (0.04871) [0.26429]	0.032465 (0.05541) [0.58591]	0.029354 (0.06463) [0.45417]	0.036055 (0.03796) [0.94971]	-0.133481 (0.09385) [-1.42226]
FTSE_3002(-11)	0.037163 (0.17444) [0.21304]	-0.049672 (0.10129) [-0.49042]	-0.016771 (0.05014) [-0.33447]	0.105800 (0.05704) [1.85488]	0.019679 (0.06653) [0.29578]	-0.042320 (0.03908) [-1.08290]	-0.119344 (0.09661) [-1.23531]
FTSE_3002(-12)	0.122596 (0.16986) [0.72173]	0.248944 (0.09863) [2.52412]	0.022642 (0.04883) [0.46374]	-0.046377 (0.05554) [-0.83500]	-0.033127 (0.06479) [-0.51133]	0.033224 (0.03805) [0.87308]	0.002284 (0.09407) [0.02428]
FTSE_3002(-13)	-0.076237 (0.17253) [-0.44187]	0.004159 (0.10017) [0.04152]	0.013902 (0.04959) [0.28033]	-0.032857 (0.05641) [-0.58242]	-0.076478 (0.06580) [-1.16222]	-0.033271 (0.03865) [-0.86079]	0.056101 (0.09555) [0.58713]
FTSE_3002(-14)	0.041802 (0.16757)	0.151853 (0.09729)	-0.005391 (0.04817)	0.079154 (0.05479)	0.073034 (0.06391)	-0.020710 (0.03754)	-0.073897 (0.09280)

	[0.24946]	[1.56076]	[-0.11193]	[1.44464]	[1.14275]	[-0.55168]	[-0.79627]
FTSE 3002(-15)	0.166811 (0.16676) [1.00032]	0.064672 (0.09682) [0.66794]	-0.100377 (0.04793) [-2.09413]	-0.135927 (0.05453) [-2.49287]	-0.087171 (0.06360) [-1.37057]	-0.058012 (0.03736) [-1.55285]	-0.074792 (0.09235) [-0.80984]
FTSE 3002(-16)	-0.143559 (0.16815) [-0.85378]	0.132959 (0.09763) [1.36188]	-0.023962 (0.04833) [-0.49578]	0.105620 (0.05498) [1.92106]	0.103382 (0.06413) [1.61204]	-0.001686 (0.03767) [-0.04476]	0.148923 (0.09312) [1.59920]
FTSE 3002(-17)	0.152957 (0.16838) [0.90839]	0.191716 (0.09777) [1.96098]	-0.006152 (0.04840) [-0.12712]	0.061006 (0.05506) [1.10805]	0.081936 (0.06422) [1.27585]	-0.046046 (0.03772) [-1.22067]	-0.009236 (0.09325) [-0.09905]
FTSE 3002(-18)	0.009637 (0.16281) [0.05919]	0.084091 (0.09453) [0.88958]	-0.093223 (0.04680) [-1.99206]	-0.004641 (0.05323) [-0.08718]	-0.018800 (0.06210) [-0.30276]	0.001146 (0.03647) [0.03142]	-0.117861 (0.09017) [-1.30714]
FTSE_3002(-19)	0.034124 (0.16295) [0.20941]	0.103485 (0.09461) [1.09377]	0.100886 (0.04684) [2.15390]	0.126332 (0.05328) [2.37100]	0.102940 (0.06215) [1.65630]	0.043240 (0.03651) [1.18446]	0.079409 (0.09025) [0.87991]
FTSE 3002(-20)	-0.139686 (0.15687) [-0.89048]	-0.123626 (0.09108) [-1.35734]	0.029508 (0.04509) [0.65443]	-0.022214 (0.05129) [-0.43310]	-0.030167 (0.05983) [-0.50422]	-0.004029 (0.03514) [-0.11465]	-0.037317 (0.08688) [-0.42955]
FTSE 3002(-21)	0.042848 (0.16367) [0.26180]	0.065502 (0.09503) [0.68930]	0.075563 (0.04704) [1.60623]	0.123959 (0.05351) [2.31635]	0.109171 (0.06242) [1.74890]	0.027671 (0.03667) [0.75468]	0.112029 (0.09064) [1.23595]
GAS2(-1)	-0.068204 (0.07724) [-0.88306]	-0.073997 (0.04484) [-1.65007]	0.070868 (0.02220) [3.19220]	0.128067 (0.02525) [5.07111]	0.163622 (0.02946) [5.55446]	-0.028061 (0.01730) [-1.62173]	0.025949 (0.04277) [0.60665]
GAS2(-2)	0.014419 (0.07727) [0.18660]	-0.007100 (0.04487) [-0.15825]	-0.026493 (0.02221) [-1.19279]	0.041458 (0.02527) [1.64083]	0.029847 (0.02947) [1.01275]	0.023343 (0.01731) [1.34845]	-0.114281 (0.04280) [-2.67041]
GAS2(-3)	-0.045777 (0.07985) [-0.57332]	-0.029659 (0.04636) [-0.63976]	-0.023026 (0.02295) [-1.00330]	0.052958 (0.02611) [2.02845]	0.064883 (0.03045) [2.13057]	-0.031444 (0.01789) [-1.75789]	-0.056469 (0.04422) [-1.27699]
GAS2(-4)	-0.093309 (0.07633) [-1.22251]	-0.040999 (0.04432) [-0.92514]	-0.050218 (0.02194) [-2.28897]	0.004539 (0.02496) [0.18186]	0.010021 (0.02911) [0.34424]	0.045319 (0.01710) [2.65035]	-0.152274 (0.04227) [-3.60233]
GAS2(-5)	-0.001544 (0.07697) [-0.02006]	-0.028922 (0.04469) [-0.64719]	0.030945 (0.02212) [1.39874]	0.005022 (0.02517) [0.19956]	0.018112 (0.02936) [0.61697]	-0.038110 (0.01724) [-2.21020]	-0.057878 (0.04263) [-1.35779]
GAS2(-6)	-0.038909 (0.07860) [-0.49501]	-0.019114 (0.04564) [-0.41881]	0.039084 (0.02259) [1.72992]	-0.002300 (0.02570) [-0.08951]	0.017196 (0.02998) [0.57361]	0.032892 (0.01761) [1.86792]	0.038425 (0.04353) [0.88269]
GAS2(-7)	-0.021644 (0.07820) [-0.27679]	-0.003334 (0.04540) [-0.07343]	0.020809 (0.02248) [0.92582]	0.013998 (0.02557) [0.54746]	0.027912 (0.02982) [0.93589]	-0.005776 (0.01752) [-0.32974]	-0.035564 (0.04331) [-0.82120]
GAS2(-8)	-0.027864 (0.07960) [-0.35006]	-0.013770 (0.04622) [-0.29794]	0.023279 (0.02288) [1.01744]	-0.055310 (0.02603) [-2.12511]	-0.066399 (0.03036) [-2.18713]	0.022403 (0.01783) [1.25631]	-0.047626 (0.04408) [-1.08036]
GAS2(-9)	0.029982 (0.07881) [0.38045]	-0.031170 (0.04576) [-0.68122]	-0.032997 (0.02265) [-1.45668]	-0.047169 (0.02577) [-1.83052]	-0.071519 (0.03006) [-2.37944]	-0.032971 (0.01765) [-1.86754]	-0.059221 (0.04364) [-1.35687]
GAS2(-10)	-0.069346 (0.07772) [-0.89223]	-0.058138 (0.04513) [-1.28834]	0.055723 (0.02234) [2.49431]	0.022538 (0.02541) [0.88685]	-0.001250 (0.02964) [-0.04218]	-0.014484 (0.01741) [-0.83185]	-0.059560 (0.04304) [-1.38371]
GAS2(-11)	-0.001510 (0.07874) [-0.01918]	-0.017886 (0.04572) [-0.39121]	0.022565 (0.02263) [0.99696]	-0.030403 (0.02575) [-1.18086]	-0.050040 (0.03003) [-1.66621]	-0.005439 (0.01764) [-0.30834]	-0.061990 (0.04361) [-1.42149]
GAS2(-12)	0.042900 (0.07763) [0.55266]	0.040530 (0.04507) [0.89926]	0.023749 (0.02231) [1.06439]	-0.004244 (0.02538) [-0.16722]	-0.015721 (0.02961) [-0.53099]	-0.038803 (0.01739) [-2.23133]	-0.083329 (0.04299) [-1.93831]
GAS2(-13)	0.023455 (0.07942) [0.29532]	-0.042926 (0.04611) [-0.93089]	0.028643 (0.02283) [1.25472]	-0.031682 (0.02597) [-1.22000]	-0.037105 (0.03029) [-1.22495]	-0.022442 (0.01779) [-1.26130]	-4.67E-05 (0.04398) [-0.00106]
GAS2(-14)	0.024733 (0.07973) [0.31020]	-0.032615 (0.04629) [-0.70451]	0.015280 (0.02292) [0.66672]	0.005959 (0.02607) [0.22855]	0.004582 (0.03041) [0.15067]	-0.037959 (0.01786) [-2.12507]	-0.016095 (0.04416) [-0.36449]
GAS2(-15)	-0.009016 (0.07956) [-0.11333]	-0.056605 (0.04619) [-1.22543]	0.065377 (0.02287) [2.85899]	-0.047888 (0.02601) [-1.84094]	-0.054035 (0.03034) [-1.78081]	0.020612 (0.01782) [1.15652]	0.036218 (0.04406) [0.82203]
GAS2(-16)	0.022327 (0.07393) [0.30199]	0.014008 (0.04293) [0.32633]	-0.045582 (0.02125) [-2.14499]	-0.035804 (0.02417) [-1.48111]	-0.023492 (0.02820) [-0.83313]	-0.025096 (0.01656) [-1.51526]	-0.053037 (0.04094) [-1.29534]
GAS2(-17)	-0.028118 (0.07331) [-0.38353]	-0.041525 (0.04257) [-0.97552]	0.028439 (0.02107) [1.34955]	0.016004 (0.02397) [0.66762]	0.049553 (0.02796) [1.77217]	-0.013261 (0.01642) [-0.80739]	0.047544 (0.04060) [1.17096]

GAS2(-18)	-0.035941 (0.07241) [-0.49633]	-0.105652 (0.04204) [-2.51289]	-0.019910 (0.02081) [-0.95658]	-0.026148 (0.02368) [-1.10436]	-0.027269 (0.02762) [-0.98734]	-0.025846 (0.01622) [-1.59323]	-0.006808 (0.04010) [-0.16976]
GAS2(-19)	0.027685 (0.07157) [0.38682]	-0.032592 (0.04156) [-0.78430]	-0.011928 (0.02057) [-0.57981]	-0.008817 (0.02340) [-0.37677]	-0.019838 (0.02730) [-0.72674]	-0.004428 (0.01603) [-0.27618]	-0.044059 (0.03964) [-1.11154]
GAS2(-20)	-0.027864 (0.07102) [-0.39234]	-0.021642 (0.04124) [-0.52484]	0.025736 (0.02041) [1.26073]	0.008104 (0.02322) [0.34900]	0.017206 (0.02709) [0.63521]	-0.030919 (0.01591) [-1.94334]	-0.024948 (0.03933) [-0.63429]
GAS2(-21)	-0.038675 (0.07233) [-0.53471]	-0.032612 (0.04200) [-0.77656]	0.004700 (0.02079) [0.22608]	0.001078 (0.02365) [0.04557]	0.000542 (0.02759) [0.01965]	0.001390 (0.01620) [0.08580]	0.025282 (0.04006) [0.63113]
C	-0.007700 (0.00473) [-1.62694]	-0.000293 (0.00275) [-0.10674]	0.001994 (0.00136) [1.46595]	-0.001645 (0.00155) [-1.06279]	-0.002452 (0.00181) [-1.35819]	0.001489 (0.00106) [1.40431]	0.002221 (0.00262) [0.84738]
TEMP	0.000506 (0.00033) [1.51608]	9.17E-05 (0.00019) [0.47296]	-0.000151 (9.6E-05) [-1.57202]	9.40E-05 (0.00011) [0.86105]	0.000154 (0.00013) [1.21213]	-2.43E-05 (7.5E-05) [-0.32497]	-9.77E-05 (0.00018) [-0.52854]
R-squared	0.279998	0.308461	0.251699	0.245866	0.226639	0.264466	0.215922
Adj. R-squared	0.118053	0.152917	0.083388	0.076243	0.052691	0.099026	0.039564
Sum sq. resids	2.153301	0.725915	0.177905	0.230218	0.313234	0.108071	0.660457
S.E. equation	0.057206	0.033215	0.016443	0.018705	0.021818	0.012816	0.031682
F-statistic	1.728966	1.983116	1.495442	1.449488	1.302915	1.598566	1.224337
Log likelihood	1246.187	1684.923	2252.317	2148.305	2024.058	2453.448	1723.054
Akaike AIC	-2.719176	-3.806500	-5.212682	-4.954906	-4.646983	-5.711147	-3.901000
Schwarz SC	-1.852627	-2.939951	-4.346133	-4.088357	-3.780434	-4.844598	-3.034451
Mean dependent	-0.003164	-0.000423	6.24E-05	-0.000801	-0.000718	0.000663	-9.53E-05
S.D. dependent	0.060914	0.036088	0.017175	0.019462	0.022417	0.013502	0.032328
Determinant resid covariance (dof adj.)	3.06E-24						
Determinant resid covariance	7.33E-25						
Log likelihood	14408.00						
Akaike information criterion	-33.12267						
Schwarz criterion	-27.05682						

B California data

B.1 Econometric data tests

Stationarity data analysis

Below we present the results of unit root testing. We use the Augmented Dickey-Fuller (1979) test, with the MacKinnon (1996) one-sided p-values. For lag selection we consider the Akaike Info Criterion.

Variable (levels)	Integration order	Differentiated variable t-stat
log(CO2)	I(1) (p= 0.082)	-22.86136
log(coal)	I(1)	-5.749465
log(gas)	I(1)	-25.30623
log(ele)	I(1)	-9.892849
log(gasoline)	I(0)	-25.00067
log(oil)	I(1)	-14.47430
log(econ)	I(1)	-22.64139

One variable (gasoline) proved to be stationary in levels at 1% significance. Also, the log(CO2) variable may be considered stationary at 10% significance. Other unit root tests such as Phillips-Perron (1988) and Kwiatkowski, Phillips, Schmidt, and Shin (KPSS, 1992) yield similar results except: log(CO2) is I(1) by both PP and KPSS tests, and log(ele) is I(0) at 1% significance by PP.

As in the EU data, we consider first differences in all variables for clearer interpretation.

B.2 VAR Granger Causality/Block Exogeneity Wald Tests

VAR Granger Causality/Block Exogeneity Wald Tests

Date: 01/14/14 Time: 13:15

Sample: 8/29/2011 11/08/2013

Included observations: 296

Dependent variable: D_LOG_CAA

Excluded	Chi-sq	df	Prob.
D_LOG_COAL	20.96384	18	0.2812
D_LOG_DJU	17.80549	18	0.4685
D_LOG_ELE_SP	29.29311	18	0.0449
D_LOG_GAS	32.22635	18	0.0207
D_LOG_OIL	35.87685	18	0.0073
D_LOG_GASO-LINE	17.77699	18	0.4704
All	144.7298	108	0.0106

Dependent variable: D_LOG_COAL

Excluded	Chi-sq	df	Prob.
D_LOG_CAA	37.48191	18	0.0045
D_LOG_DJU	17.80876	18	0.4683
D_LOG_ELE_SP	12.59947	18	0.8148
D_LOG_GAS	21.72335	18	0.2445
D_LOG_OIL	12.81355	18	0.8025
D_LOG_GASO-LINE	11.21878	18	0.8848
All	113.5918	108	0.3375

Dependent variable: D_LOG_DJU

Excluded	Chi-sq	df	Prob.
D_LOG_CAA	27.62074	18	0.0681
D_LOG_COAL	17.61279	18	0.4814
D_LOG_ELE_SP	23.59380	18	0.1688
D_LOG_GAS	16.85315	18	0.5332
D_LOG_OIL	30.60599	18	0.0320
D_LOG_GASO-LINE	16.67131	18	0.5458
All	145.5405	108	0.0094

Dependent variable: D_LOG_ELE_SP

Excluded	Chi-sq	df	Prob.
----------	--------	----	-------

D_LOG_CAA	20.38678	18	0.3115
D_LOG_COAL	14.91241	18	0.6680
D_LOG_DJU	16.99739	18	0.5233
D_LOG_GAS	11.01013	18	0.8939
D_LOG_OIL	13.62319	18	0.7533
D_LOG_GASO-LINE	16.05764	18	0.5885
All	100.3411	108	0.6873

Dependent variable: D_LOG_GAS

Excluded	Chi-sq	df	Prob.
D_LOG_CAA	20.29620	18	0.3164
D_LOG_COAL	32.34413	18	0.0200
D_LOG_DJU	24.89972	18	0.1277
D_LOG_ELE_SP	22.09861	18	0.2276
D_LOG_OIL	20.33053	18	0.3145
D_LOG_GASO-LINE	15.84148	18	0.6036
All	114.8570	108	0.3078

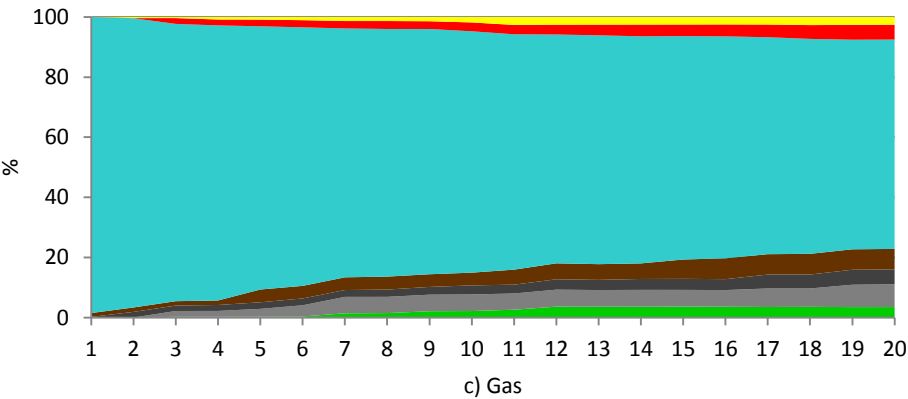
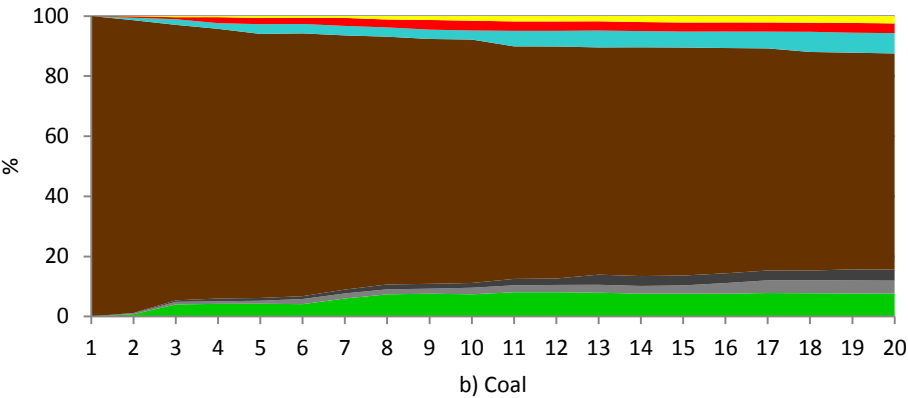
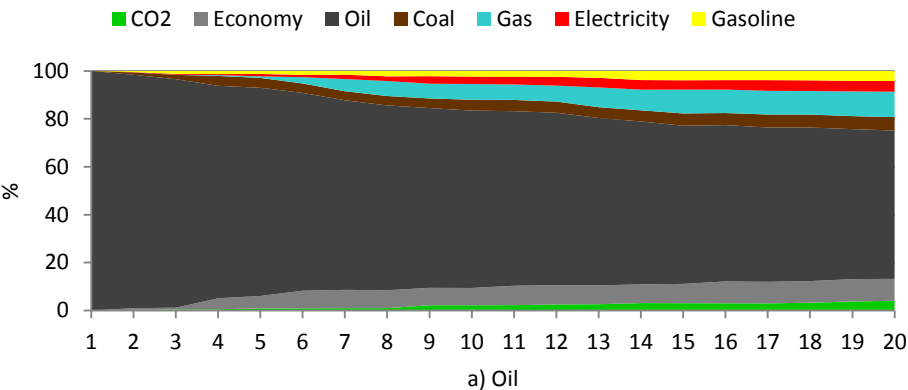
Dependent variable: D_LOG_OIL

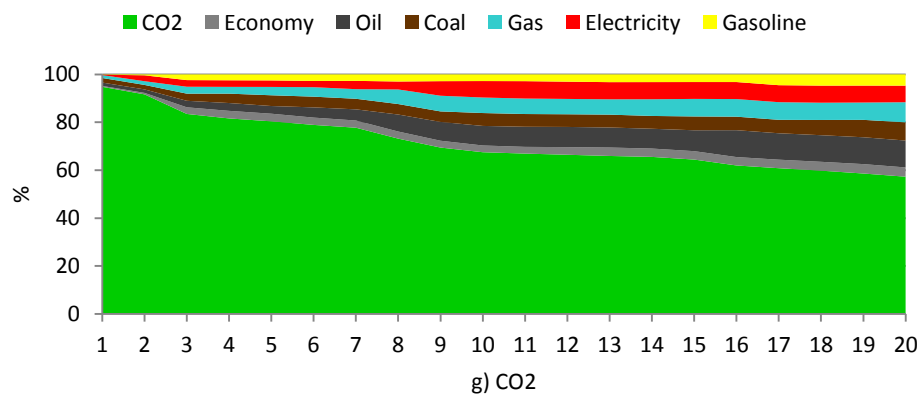
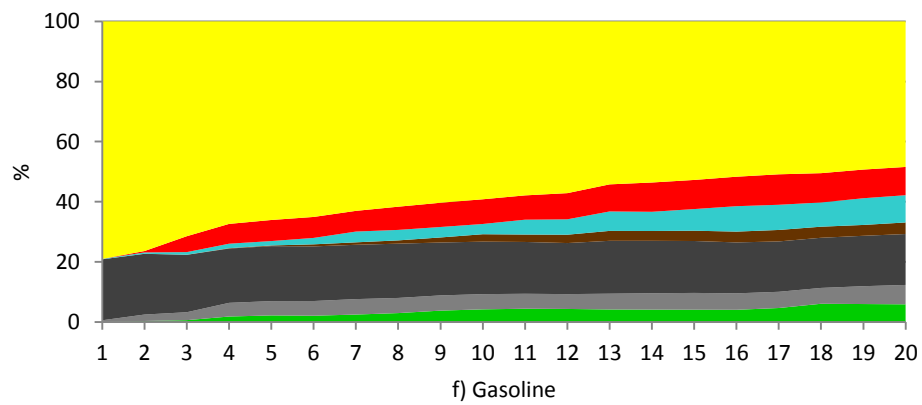
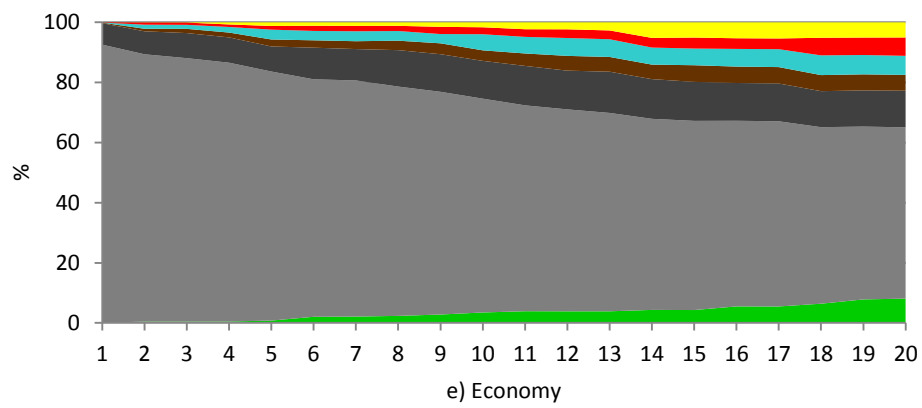
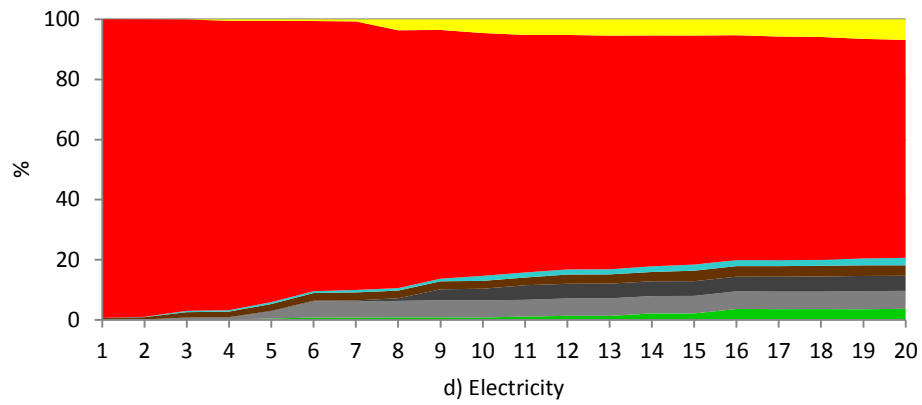
Excluded	Chi-sq	df	Prob.
D_LOG_CAA	22.85033	18	0.1964
D_LOG_COAL	18.80698	18	0.4038
D_LOG_DJU	25.13761	18	0.1212
D_LOG_ELE_SP	16.34569	18	0.5684
D_LOG_GAS	34.15995	18	0.0120
D_LOG_GASO-LINE	21.76638	18	0.2425
All	127.7595	108	0.0943

Dependent variable: D_LOG_GASOLINE

Excluded	Chi-sq	df	Prob.
D_LOG_CAA	28.41049	18	0.0561
D_LOG_COAL	19.78169	18	0.3452
D_LOG_DJU	23.18929	18	0.1834
D_LOG_ELE_SP	29.75646	18	0.0399
D_LOG_GAS	30.00693	18	0.0374
D_LOG_OIL	12.46348	18	0.8224
All	133.3138	108	0.0497

B.3 Variance decomposition





B.4 VAR output

Vector Autoregression Estimates

Date: 01/14/14 Time: 13:15

Sample (adjusted): 9/26/2011 11/04/2013

Included observations: 296 after adjustments

Standard errors in () & t-statistics in []

	D_LOG_CAA	D_LOG_COAL	D_LOG_DJU	D_LOG_ELE_SP	D_LOG_GAS	D_LOG_OIL	D_LOG_GASO- LINE
D_LOG_CAA(-1)	0.020549 (0.07107) [0.28914]	-0.165994 (0.12818) [-1.29504]	0.033317 (0.03335) [0.99895]	0.113095 (0.50480) [0.22404]	-0.009276 (0.11951) [-0.07762]	-0.058432 (0.07407) [-0.78887]	-0.113494 (0.13483) [-0.84175]
D_LOG_CAA(-2)	0.041446 (0.06934) [0.59771]	-0.342952 (0.12506) [-2.74234]	-0.004850 (0.03254) [-0.14904]	-0.320895 (0.49252) [-0.65153]	0.112739 (0.11660) [0.96688]	0.028707 (0.07227) [0.39722]	0.103898 (0.13155) [0.78979]
D_LOG_CAA(-3)	-0.002041 (0.07179) [-0.02843]	0.141561 (0.12947) [1.09341]	-0.019241 (0.03369) [-0.57117]	-0.164771 (0.50989) [-0.32315]	0.018594 (0.12071) [0.15404]	0.024425 (0.07482) [0.32646]	0.248589 (0.13619) [1.82532]
D_LOG_CAA(-4)	-0.122116 (0.07278) [-1.67792]	0.159529 (0.13126) [1.21538]	0.026352 (0.03415) [0.77157]	-0.681512 (0.51694) [-1.31836]	0.041849 (0.12238) [0.34196]	-0.082351 (0.07585) [-1.08568]	-0.100298 (0.13807) [-0.72641]
D_LOG_CAA(-5)	0.153475 (0.07361) [2.08489]	-0.013984 (0.13276) [-0.10533]	0.055830 (0.03455) [1.61612]	0.686263 (0.52287) [1.31249]	0.037414 (0.12378) [0.30225]	-0.083090 (0.07672) [-1.08300]	-0.068388 (0.13966) [-0.48969]
D_LOG_CAA(-6)	-0.015145 (0.07503) [-0.20186]	0.228489 (0.13531) [1.68861]	-0.000708 (0.03521) [-0.02011]	-0.098917 (0.53291) [-0.18562]	0.279165 (0.12616) [2.21278]	0.118559 (0.07819) [1.51621]	-0.073413 (0.14234) [-0.51577]
D_LOG_CAA(-7)	-0.074988 (0.07382) [-1.01579]	0.410234 (0.13314) [3.08119]	0.047295 (0.03464) [1.36518]	-0.246670 (0.52436) [-0.47042]	-0.189472 (0.12414) [-1.52632]	0.006436 (0.07694) [0.08364]	-0.170396 (0.14005) [-1.21665]
D_LOG_CAA(-8)	-0.035875 (0.07374) [-0.48647]	-0.209220 (0.13300) [-1.57307]	-0.016407 (0.03461) [-0.47408]	0.292198 (0.52381) [0.55784]	0.102090 (0.12401) [0.82327]	0.136644 (0.07686) [1.77785]	0.292765 (0.13991) [2.09257]
D_LOG_CAA(-9)	0.077271 (0.07296) [1.05914]	-0.213116 (0.13158) [-1.61967]	0.048307 (0.03424) [1.41094]	0.128131 (0.51821) [0.24726]	0.043686 (0.12268) [0.35609]	0.096436 (0.07604) [1.26826]	0.188040 (0.13841) [1.35856]
D_LOG_CAA(-10)	0.091984 (0.06504) [1.41416]	-0.145499 (0.11731) [-1.24029]	0.025296 (0.03052) [0.82871]	-0.076059 (0.46201) [-0.16463]	0.023020 (0.10938) [0.21047]	0.098171 (0.06779) [1.44812]	0.094201 (0.12340) [0.76337]
D_LOG_CAA(-11)	-0.003973 (0.06528) [-0.06086]	-0.052128 (0.11774) [-0.44274]	0.025314 (0.03064) [0.82625]	0.431678 (0.46370) [0.93094]	0.185057 (0.10978) [1.68575]	-0.126188 (0.06804) [-1.85461]	-0.004580 (0.12385) [-0.03698]
D_LOG_CAA(-12)	-0.072051 (0.06370) [-1.13106]	-0.148330 (0.11489) [-1.29108]	-0.038888 (0.02989) [-1.30083]	0.645787 (0.45247) [1.42724]	0.010372 (0.10712) [0.09683]	-0.029761 (0.06639) [-0.44826]	0.022158 (0.12085) [0.18335]
D_LOG_CAA(-13)	0.140701 (0.06057) [2.32312]	0.080941 (0.10923) [0.74101]	-0.035507 (0.02842) [-1.24924]	-0.243848 (0.43019) [-0.56683]	-0.117388 (0.10184) [-1.15263]	-0.089154 (0.06312) [-1.41239]	0.056549 (0.11490) [0.49214]
D_LOG_CAA(-14)	-0.011779 (0.05872) [-0.20060]	0.065889 (0.10591) [0.62215]	0.041161 (0.02756) [1.49363]	0.822460 (0.41710) [1.97186]	0.047492 (0.09874) [0.48096]	0.036406 (0.06120) [0.59486]	0.207121 (0.11141) [1.85917]
D_LOG_CAA(-15)	-0.100271 (0.06102) [-1.64330]	-0.075559 (0.11005) [-0.68660]	0.031880 (0.02863) [1.11333]	1.310807 (0.43341) [3.02442]	0.132871 (0.10260) [1.29497]	-0.018104 (0.06359) [-0.28467]	-0.033005 (0.11576) [-0.28512]
D_LOG_CAA(-16)	0.010214 (0.06462) [0.15805]	-0.141639 (0.11655) [-1.21528]	0.019170 (0.03033) [0.63214]	-0.011630 (0.45901) [-0.02534]	-0.092821 (0.10867) [-0.85418]	0.038852 (0.06735) [0.57686]	-0.291642 (0.12260) [-2.37881]

D_LOG_CAA(-17)	0.187003 (0.06558) [2.85156]	0.006033 (0.11827) [0.05101]	0.028801 (0.03078) [0.93585]	-0.195896 (0.46581) [-0.42055]	-0.226916 (0.11028) [-2.05772]	-0.025013 (0.06835) [-0.36596]	0.233433 (0.12442) [1.87624]
D_LOG_CAA(-18)	0.029156 (0.06556) [0.44475]	-0.060785 (0.11823) [-0.51411]	-0.077515 (0.03076) [-2.51963]	0.337868 (0.46564) [0.72560]	0.216974 (0.11024) [1.96826]	-0.037666 (0.06832) [-0.55128]	0.050731 (0.12437) [0.40790]
D_LOG_COAL(-1)	0.004994 (0.04281) [0.11665]	0.014277 (0.07722) [0.18489]	-0.018072 (0.02009) [-0.89946]	-0.112228 (0.30410) [-0.36904]	0.058170 (0.07199) [0.80799]	-0.048108 (0.04462) [-1.07813]	0.030697 (0.08123) [0.37793]
D_LOG_COAL(-2)	-0.072404 (0.04208) [-1.72048]	0.132804 (0.07590) [1.74974]	-0.018526 (0.01975) [-0.93806]	-0.225943 (0.29892) [-0.75586]	0.023889 (0.07077) [0.33757]	-0.056845 (0.04386) [-1.29602]	-0.020690 (0.07984) [-0.25914]
D_LOG_COAL(-3)	-0.076543 (0.04146) [-1.84608]	0.093670 (0.07478) [1.25264]	-0.007575 (0.01946) [-0.38930]	-0.042506 (0.29451) [-0.14433]	-0.003412 (0.06972) [-0.04893]	-0.097421 (0.04321) [-2.25442]	-0.045047 (0.07866) [-0.57266]
D_LOG_COAL(-4)	-0.025359 (0.04240) [-0.59807]	-0.031245 (0.07647) [-0.40859]	-0.025975 (0.01990) [-1.30539]	0.277334 (0.30117) [0.92084]	0.192256 (0.07130) [2.69644]	0.031935 (0.04419) [0.72265]	-0.024486 (0.08044) [-0.30439]
D_LOG_COAL(-5)	-0.031015 (0.04288) [-0.72321]	0.166017 (0.07734) [2.14647]	0.015938 (0.02013) [0.79193]	0.037482 (0.30461) [0.12305]	0.016713 (0.07211) [0.23176]	0.029915 (0.04470) [0.66931]	0.116012 (0.08136) [1.42591]
D_LOG_COAL(-6)	0.015667 (0.04233) [0.37015]	0.003507 (0.07634) [0.04594]	0.021719 (0.01986) [1.09343]	-0.109055 (0.30064) [-0.36274]	0.010505 (0.07117) [0.14759]	-0.019609 (0.04411) [-0.44452]	0.056942 (0.08030) [0.70912]
D_LOG_COAL(-7)	0.010879 (0.04227) [0.25737]	-0.037602 (0.07624) [-0.49324]	-0.019620 (0.01984) [-0.98908]	0.127198 (0.30025) [0.42364]	-0.032995 (0.07108) [-0.46419]	-0.052486 (0.04406) [-1.19135]	-0.091667 (0.08019) [-1.14306]
D_LOG_COAL(-8)	0.046228 (0.04165) [1.10997]	-0.013014 (0.07511) [-0.17326]	-0.021454 (0.01954) [-1.09770]	-0.435615 (0.29582) [-1.47254]	-0.064116 (0.07003) [-0.91550]	0.026529 (0.04341) [0.61118]	0.090645 (0.07901) [1.14721]
D_LOG_COAL(-9)	0.070042 (0.04222) [1.65883]	-0.096389 (0.07615) [-1.26575]	-0.004661 (0.01982) [-0.23521]	-0.111170 (0.29991) [-0.37067]	0.040687 (0.07100) [0.57304]	-0.004113 (0.04401) [-0.09346]	-0.132059 (0.08011) [-1.64855]
D_LOG_COAL(-10)	-0.028985 (0.04155) [-0.69753]	-0.055670 (0.07494) [-0.74283]	-0.025508 (0.01950) [-1.30806]	-0.001456 (0.29516) [-0.00493]	0.130990 (0.06988) [1.87462]	0.013272 (0.04331) [0.30645]	0.043687 (0.07884) [0.55415]
D_LOG_COAL(-11)	-0.012628 (0.04174) [-0.30257]	0.062349 (0.07527) [0.82832]	-0.020458 (0.01959) [-1.04452]	0.577041 (0.29645) [1.94653]	-0.131974 (0.07018) [-1.88049]	0.026995 (0.04350) [0.62061]	0.094414 (0.07918) [1.19240]
D_LOG_COAL(-12)	0.026437 (0.04192) [0.63061]	0.034977 (0.07561) [0.46259]	0.029934 (0.01967) [1.52151]	-0.174150 (0.29778) [-0.58483]	-0.089391 (0.07050) [-1.26802]	0.016907 (0.04369) [0.38694]	0.123042 (0.07954) [1.54700]
D_LOG_COAL(-13)	0.026976 (0.04175) [0.64615]	-0.186648 (0.07530) [-2.47886]	-0.017490 (0.01959) [-0.89268]	0.275123 (0.29654) [0.92777]	0.103602 (0.07020) [1.47574]	-0.040665 (0.04351) [-0.93457]	0.009929 (0.07921) [0.12536]
D_LOG_COAL(-14)	-0.002418 (0.04213) [-0.05738]	-0.140884 (0.07599) [-1.85404]	0.015010 (0.01977) [0.75916]	0.377888 (0.29927) [1.26272]	0.198742 (0.07085) [2.80518]	0.087825 (0.04391) [2.00002]	0.124385 (0.07993) [1.55611]
D_LOG_COAL(-15)	0.049000 (0.04257) [1.15101]	0.068167 (0.07678) [0.88784]	0.002888 (0.01998) [0.14456]	-0.206656 (0.30238) [-0.68343]	-0.094260 (0.07159) [-1.31675]	-0.047010 (0.04437) [-1.05954]	-0.122153 (0.08076) [-1.51246]
D_LOG_COAL(-16)	-0.036075 (0.04257) [-0.84738]	0.086124 (0.07678) [1.12169]	-0.005727 (0.01998) [-0.28667]	0.385706 (0.30239) [1.27553]	0.054557 (0.07159) [0.76210]	-0.034899 (0.04437) [-0.78653]	0.035736 (0.08077) [0.44246]
D_LOG_COAL(-17)	0.028875 (0.04109) [0.70273]	0.053223 (0.07411) [0.71820]	-0.000979 (0.01928) [-0.05079]	0.237097 (0.29186) [0.81237]	0.058875 (0.06909) [0.85209]	-0.005325 (0.04282) [-0.12433]	0.007294 (0.07795) [0.09357]
D_LOG_COAL(-18)	0.069909 (0.04011) [1.74309]	0.032916 (0.07233) [0.45506]	-0.025232 (0.01882) [-1.34059]	0.082689 (0.28488) [0.29026]	-0.023685 (0.06744) [-0.35120]	-0.004564 (0.04180) [-0.10918]	-0.049115 (0.07609) [-0.64549]
D_LOG_DJU(-1)	-0.129377	-0.186655	0.047973	0.318011	-0.080157	0.190658	0.533481

	(0.16490) [-0.78458]	(0.29740) [-0.62762]	(0.07739) [0.61992]	(1.17128) [0.27151]	(0.27729) [-0.28907]	(0.17186) [1.10935]	(0.31285) [1.70525]
D_LOG_DJU(-2)	0.397267 (0.16907) [2.34973]	0.317940 (0.30492) [1.04270]	0.034816 (0.07934) [0.43881]	1.193915 (1.20089) [0.99419]	0.502663 (0.28430) [1.76808]	-0.044603 (0.17621) [-0.25312]	-0.383313 (0.32075) [-1.19504]
D_LOG_DJU(-3)	0.137128 (0.16854) [0.81360]	0.149675 (0.30398) [0.49239]	0.036872 (0.07910) [0.46616]	0.655876 (1.19717) [0.54786]	-0.092829 (0.28342) [-0.32754]	-0.511133 (0.17566) [-2.90974]	-0.752990 (0.31976) [-2.35487]
D_LOG_DJU(-4)	-0.076065 (0.16349) [-0.46525]	0.323003 (0.29486) [1.09544]	0.026208 (0.07672) [0.34159]	-1.384121 (1.16127) [-1.19191]	-0.371794 (0.27492) [-1.35238]	0.229406 (0.17039) [1.34632]	-0.158692 (0.31017) [-0.51163]
D_LOG_DJU(-5)	-0.071358 (0.15873) [-0.44956]	0.159622 (0.28627) [0.55759]	-0.132663 (0.07449) [-1.78096]	-2.785067 (1.12745) [-2.47023]	0.302446 (0.26691) [1.13313]	-0.309837 (0.16543) [-1.87289]	-0.548391 (0.30114) [-1.82106]
D_LOG_DJU(-6)	0.148541 (0.16179) [0.91810]	-0.279953 (0.29180) [-0.95941]	0.074844 (0.07593) [0.98574]	-0.356419 (1.14920) [-0.31015]	0.574690 (0.27206) [2.11235]	0.243893 (0.16862) [1.44637]	0.594051 (0.30695) [1.93536]
D_LOG_DJU(-7)	-0.172089 (0.16217) [-1.06117]	-0.071595 (0.29248) [-0.24479]	-0.148075 (0.07610) [-1.94570]	-0.509814 (1.15188) [-0.44259]	0.257063 (0.27270) [0.94267]	-0.011758 (0.16902) [-0.06956]	0.153047 (0.30766) [0.49745]
D_LOG_DJU(-8)	-0.103988 (0.16720) [-0.62194]	0.265939 (0.30155) [0.88190]	0.119726 (0.07847) [1.52584]	0.211503 (1.18762) [0.17809]	-0.516401 (0.28116) [-1.83669]	-0.143475 (0.17426) [-0.82333]	-0.118165 (0.31721) [-0.37251]
D_LOG_DJU(-9)	0.085519 (0.16073) [0.53206]	0.171060 (0.28988) [0.59010]	-0.056654 (0.07543) [-0.75108]	0.184774 (1.14167) [0.16185]	0.013093 (0.27028) [0.04844]	0.010378 (0.16752) [0.06195]	0.195053 (0.30494) [0.63965]
D_LOG_DJU(-10)	-0.057205 (0.16089) [-0.35555]	-0.524525 (0.29017) [-1.80764]	0.026812 (0.07550) [0.35510]	-0.161177 (1.14280) [-0.14104]	-0.022835 (0.27055) [-0.08440]	-0.136306 (0.16768) [-0.81287]	-0.159682 (0.30524) [-0.52314]
D_LOG_DJU(-11)	0.305602 (0.15594) [1.95970]	0.394251 (0.28125) [1.40179]	0.059342 (0.07318) [0.81088]	1.992469 (1.10766) [1.79881]	-0.214921 (0.26223) [-0.81960]	0.073734 (0.16253) [0.45367]	-0.159940 (0.29585) [-0.54061]
D_LOG_DJU(-12)	0.126481 (0.14951) [0.84595]	-0.002637 (0.26965) [-0.00978]	0.008027 (0.07016) [0.11441]	0.320720 (1.06199) [0.30200]	-0.056833 (0.25142) [-0.22605]	-0.118298 (0.15583) [-0.75916]	0.018514 (0.28365) [0.06527]
D_LOG_DJU(-13)	-0.083038 (0.15271) [-0.54376]	0.181838 (0.27542) [0.66022]	-0.028605 (0.07167) [-0.39915]	0.109248 (1.08470) [0.10072]	-0.563472 (0.25679) [-2.19426]	0.001618 (0.15916) [0.01016]	-0.288071 (0.28972) [-0.99431]
D_LOG_DJU(-14)	-0.076446 (0.15647) [-0.48856]	0.153720 (0.28220) [0.54472]	-0.149990 (0.07343) [-2.04262]	-1.054084 (1.11141) [-0.94842]	-0.152848 (0.26312) [-0.58091]	-0.089955 (0.16308) [-0.55160]	-0.189654 (0.29685) [-0.63888]
D_LOG_DJU(-15)	0.129936 (0.15877) [0.81838]	0.524372 (0.28635) [1.83124]	0.085754 (0.07451) [1.15091]	-0.998504 (1.12775) [-0.88540]	-0.121228 (0.26698) [-0.45407]	0.387600 (0.16548) [2.34233]	0.162573 (0.30122) [0.53972]
D_LOG_DJU(-16)	-0.073332 (0.15721) [-0.46646]	0.493910 (0.28353) [1.74199]	-0.019917 (0.07378) [-0.26997]	-0.776806 (1.11665) [-0.69566]	0.400086 (0.26436) [1.51344]	0.197887 (0.16385) [1.20774]	0.011728 (0.29825) [0.03932]
D_LOG_DJU(-17)	0.030398 (0.15731) [0.19323]	0.016978 (0.28372) [0.05984]	0.077332 (0.07382) [1.04752]	-0.342319 (1.11738) [-0.30636]	-0.052440 (0.26453) [-0.19824]	0.072803 (0.16395) [0.44404]	-0.302764 (0.29845) [-1.01446]
D_LOG_DJU(-18)	0.142664 (0.15503) [0.92025]	0.112215 (0.27960) [0.40134]	0.048420 (0.07275) [0.66554]	-1.639605 (1.10116) [-1.48898]	0.491963 (0.26069) [1.88717]	0.190250 (0.16157) [1.17747]	-0.043665 (0.29412) [-0.14846]
D_LOG_ELE_SP(-1)	-0.021478 (0.01060) [-2.02570]	0.018645 (0.01912) [0.97504]	-0.005760 (0.00498) [-1.15764]	0.046348 (0.07531) [0.61541]	0.005595 (0.01783) [0.31381]	-0.005584 (0.01105) [-0.50530]	-0.018130 (0.02012) [-0.90127]
D_LOG_ELE_SP(-2)	-0.012038 (0.01090) [-1.10427]	-0.016297 (0.01966) [-0.82892]	-3.44E-06 (0.00512) [-0.00067]	-0.473187 (0.07743) [-6.11116]	0.031847 (0.01833) [1.73732]	0.006717 (0.01136) [0.59125]	0.062245 (0.02068) [3.00973]
D_LOG_ELE_SP(-3)	-0.008157 (0.01222)	0.029565 (0.02204)	-0.002551 (0.00574)	-0.352288 (0.08682)	0.005763 (0.02055)	-0.003374 (0.01274)	-0.046026 (0.02319)

	[-0.66735]	[1.34117]	[-0.44475]	[-4.05780]	[0.28041]	[-0.26489]	[-1.98486]
D_LOG_ELE_SP(-4)	-0.020645 (0.01277) [-1.61631]	0.014334 (0.02304) [0.62226]	0.002028 (0.00599) [0.33837]	-0.193414 (0.09072) [-2.13187]	0.029327 (0.02148) [1.36543]	0.008169 (0.01331) [0.61363]	0.049020 (0.02423) [2.02291]
D_LOG_ELE_SP(-5)	-0.010897 (0.01273) [-0.85604]	0.014098 (0.02296) [0.61407]	0.008622 (0.00597) [1.44321]	-0.144764 (0.09042) [-1.60104]	0.006576 (0.02141) [0.30723]	0.002801 (0.01327) [0.21114]	0.016755 (0.02415) [0.69376]
D_LOG_ELE_SP(-6)	0.014588 (0.01280) [1.13960]	0.022403 (0.02309) [0.97040]	0.000328 (0.00601) [0.05465]	-0.365853 (0.09092) [-4.02381]	-0.002609 (0.02152) [-0.12119]	0.018179 (0.01334) [1.36265]	-0.020670 (0.02428) [-0.85116]
D_LOG_ELE_SP(-7)	-0.015961 (0.01320) [-1.20940]	0.016732 (0.02380) [0.70297]	0.007101 (0.00619) [1.14648]	-0.063843 (0.09374) [-0.68106]	0.017151 (0.02219) [0.77283]	0.017635 (0.01375) [1.28214]	0.008206 (0.02504) [0.32775]
D_LOG_ELE_SP(-8)	-0.021840 (0.01260) [-1.73391]	-0.004925 (0.02272) [-0.21682]	-0.001151 (0.00591) [-0.19480]	-0.218303 (0.08947) [-2.44001]	-0.000386 (0.02118) [-0.01824]	-0.006056 (0.01313) [-0.46129]	0.015188 (0.02390) [0.63555]
D_LOG_ELE_SP(-9)	0.026238 (0.01265) [2.07364]	-0.003058 (0.02282) [-0.13400]	0.004829 (0.00594) [0.81326]	-0.205770 (0.08987) [-2.28954]	-0.017836 (0.02128) [-0.83826]	0.020990 (0.01319) [1.59166]	0.006672 (0.02401) [0.27794]
D_LOG_ELE_SP(-10)	-0.009414 (0.01266) [-0.74350]	0.004056 (0.02283) [0.17761]	0.003393 (0.00594) [0.57111]	-0.127106 (0.08993) [-1.41336]	-0.010949 (0.02129) [-0.51426]	0.019823 (0.01320) [1.50225]	0.047031 (0.02402) [1.95794]
D_LOG_ELE_SP(-11)	-0.004851 (0.01250) [-0.38800]	0.015646 (0.02255) [0.69388]	-0.003649 (0.00587) [-0.62187]	-0.213891 (0.08880) [-2.40859]	-0.030633 (0.02102) [-1.45709]	0.008698 (0.01303) [0.66752]	0.037751 (0.02372) [1.59159]
D_LOG_ELE_SP(-12)	0.006851 (0.01283) [0.53411]	-0.003610 (0.02314) [-0.15603]	0.009578 (0.00602) [1.59099]	-0.024684 (0.09111) [-0.27091]	0.022766 (0.02157) [1.05544]	0.029549 (0.01337) [2.21018]	0.047556 (0.02434) [1.95409]
D_LOG_ELE_SP(-13)	0.008150 (0.01238) [0.65828]	0.009673 (0.02233) [0.43322]	0.003096 (0.00581) [0.53294]	-0.075268 (0.08794) [-0.85593]	0.014544 (0.02082) [0.69862]	0.011902 (0.01290) [0.92243]	0.017153 (0.02349) [0.73032]
D_LOG_ELE_SP(-14)	0.000764 (0.01217) [0.06278]	0.047578 (0.02195) [2.16727]	0.010677 (0.00571) [1.86915]	-0.061597 (0.08646) [-0.71245]	0.003237 (0.02047) [0.15813]	-0.001359 (0.01269) [-0.10714]	0.002565 (0.02309) [0.11108]
D_LOG_ELE_SP(-15)	-0.011707 (0.01227) [-0.95387]	0.012715 (0.02214) [0.57442]	0.012628 (0.00576) [2.19241]	-0.005309 (0.08718) [-0.06089]	0.024344 (0.02064) [1.17954]	0.016054 (0.01279) [1.25507]	-0.001475 (0.02328) [-0.06335]
D_LOG_ELE_SP(-16)	-0.006764 (0.01207) [-0.56019]	0.002310 (0.02178) [0.10610]	0.000831 (0.00567) [0.14662]	-0.127147 (0.08577) [-1.48250]	-0.005847 (0.02030) [-0.28797]	-0.009893 (0.01258) [-0.78609]	-0.003011 (0.02291) [-0.13145]
D_LOG_ELE_SP(-17)	-0.001070 (0.01133) [-0.09445]	0.004551 (0.02043) [0.22283]	-0.005029 (0.00531) [-0.94619]	-0.083624 (0.08044) [-1.03955]	-0.019882 (0.01904) [-1.04402]	0.013099 (0.01180) [1.10975]	0.002927 (0.02149) [0.13623]
D_LOG_ELE_SP(-18)	0.001786 (0.01163) [0.15359]	-0.003910 (0.02098) [-0.18642]	0.002722 (0.00546) [0.49880]	-0.077490 (0.08261) [-0.93804]	0.037597 (0.01956) [1.92244]	0.004757 (0.01212) [0.39242]	0.036573 (0.02206) [1.65755]
D_LOG_GAS(-1)	0.035429 (0.04418) [0.80197]	-0.084510 (0.07968) [-1.06069]	-0.035933 (0.02073) [-1.73321]	-0.151553 (0.31379) [-0.48298]	-0.122865 (0.07429) [-1.65394]	-0.006091 (0.04604) [-0.13230]	0.068402 (0.08381) [0.81613]
D_LOG_GAS(-2)	0.075783 (0.04298) [1.76320]	-0.110813 (0.07752) [-1.42954]	-0.006115 (0.02017) [-0.30317]	-0.294926 (0.30529) [-0.96606]	0.064779 (0.07227) [0.89629]	0.018370 (0.04480) [0.41008]	-0.049723 (0.08154) [-0.60979]
D_LOG_GAS(-3)	-0.001475 (0.04215) [-0.03499]	0.079767 (0.07601) [1.04942]	-0.026949 (0.01978) [-1.36255]	-0.203424 (0.29936) [-0.67954]	-0.088320 (0.07087) [-1.24623]	-0.049833 (0.04393) [-1.13450]	0.067346 (0.07996) [0.84228]
D_LOG_GAS(-4)	-0.059445 (0.04262) [-1.39469]	0.180321 (0.07687) [2.34577]	0.029931 (0.02000) [1.49641]	0.134854 (0.30275) [0.44544]	0.042986 (0.07167) [0.59977]	-0.062042 (0.04442) [-1.39663]	0.019858 (0.08086) [0.24558]
D_LOG_GAS(-5)	-0.073869 (0.04391) [-1.68238]	0.023548 (0.07919) [0.29736]	-0.005097 (0.02061) [-0.24737]	-0.146789 (0.31187) [-0.47067]	-0.008448 (0.07383) [-0.11442]	-0.095535 (0.04576) [-2.08765]	-0.183274 (0.08330) [-2.20016]

D_LOG_GAS(-6)	-0.041504 (0.04473) [-0.92798]	-0.090474 (0.08066) [-1.12163]	0.002389 (0.02099) [0.11382]	-0.246137 (0.31768) [-0.77479]	0.095418 (0.07521) [1.26871]	0.093952 (0.04661) [2.01553]	0.194532 (0.08485) [2.29261]
D_LOG_GAS(-7)	-0.121005 (0.04536) [-2.66776]	-0.068438 (0.08181) [-0.83659]	0.007270 (0.02129) [0.34154]	0.001895 (0.32218) [0.00588]	0.130438 (0.07627) [1.71015]	-0.002845 (0.04727) [-0.06018]	0.137038 (0.08605) [1.59249]
D_LOG_GAS(-8)	0.061406 (0.04552) [1.34888]	0.022439 (0.08210) [0.27330]	-0.004310 (0.02136) [-0.20173]	-0.150077 (0.32336) [-0.46413]	0.139127 (0.07655) [1.81743]	-0.116956 (0.04745) [-2.46501]	-0.051379 (0.08637) [-0.59490]
D_LOG_GAS(-9)	-0.030453 (0.04446) [-0.68500]	-0.039391 (0.08018) [-0.49129]	0.047611 (0.02086) [2.28210]	0.625513 (0.31577) [1.98091]	0.025671 (0.07476) [0.34339]	0.063715 (0.04633) [1.37513]	0.005202 (0.08434) [0.06168]
D_LOG_GAS(-10)	-0.026343 (0.04463) [-0.59020]	-0.123872 (0.08050) [-1.53882]	0.015579 (0.02095) [0.74379]	0.093967 (0.31703) [0.29640]	-0.076826 (0.07505) [-1.02362]	-0.016679 (0.04652) [-0.35854]	0.084965 (0.08468) [1.00340]
D_LOG_GAS(-11)	0.050840 (0.04446) [1.14340]	0.026796 (0.08019) [0.33415]	-0.005321 (0.02087) [-0.25502]	0.115358 (0.31582) [0.36526]	0.058441 (0.07477) [0.78163]	0.055440 (0.04634) [1.19635]	-0.088604 (0.08436) [-1.05036]
D_LOG_GAS(-12)	-0.017273 (0.04288) [-0.40280]	-0.079292 (0.07734) [-1.02526]	-0.008074 (0.02012) [-0.40119]	0.348103 (0.30459) [1.14287]	-0.187833 (0.07211) [-2.60488]	-0.030337 (0.04469) [-0.67879]	-0.072103 (0.08135) [-0.88629]
D_LOG_GAS(-13)	-0.045019 (0.04399) [-1.02345]	0.058606 (0.07933) [0.73874]	-0.013341 (0.02064) [-0.64629]	0.132428 (0.31244) [0.42385]	-0.088411 (0.07397) [-1.19528]	0.064848 (0.04584) [1.41452]	0.044931 (0.08345) [0.53841]
D_LOG_GAS(-14)	-0.015105 (0.04588) [-0.32923]	-0.035295 (0.08275) [-0.42655]	0.018680 (0.02153) [0.86759]	0.237377 (0.32589) [0.72840]	-0.089474 (0.07715) [-1.15973]	-0.033309 (0.04782) [-0.69658]	-0.199854 (0.08704) [-2.29603]
D_LOG_GAS(-15)	-0.041845 (0.04469) [-0.93639]	-0.164197 (0.08060) [-2.03728]	-8.65E-05 (0.02097) [-0.00412]	0.051883 (0.31742) [0.16345]	-0.079579 (0.07515) [-1.05900]	-0.017758 (0.04658) [-0.38127]	0.268908 (0.08478) [3.17180]
D_LOG_GAS(-16)	-0.017991 (0.04649) [-0.38694]	-0.078459 (0.08385) [-0.93566]	0.020137 (0.02182) [0.92292]	0.087547 (0.33025) [0.26509]	0.032532 (0.07818) [0.41610]	-0.017989 (0.04846) [-0.37122]	0.061386 (0.08821) [0.69592]
D_LOG_GAS(-17)	-0.031172 (0.04744) [-0.65703]	-0.021873 (0.08557) [-0.25563]	0.008332 (0.02226) [0.37420]	-0.400209 (0.33699) [-1.18759]	-0.022402 (0.07978) [-0.28080]	-0.078020 (0.04945) [-1.57784]	-0.103522 (0.09001) [-1.15012]
D_LOG_GAS(-18)	-0.092404 (0.04717) [-1.95916]	0.071034 (0.08506) [0.83507]	-0.005760 (0.02213) [-0.26024]	-0.336528 (0.33501) [-1.00452]	0.107654 (0.07931) [1.35737]	-0.113048 (0.04916) [-2.29972]	0.018737 (0.08948) [0.20940]
D_LOG_OIL(-1)	0.073922 (0.08229) [0.89828]	-0.064804 (0.14842) [-0.43663]	-0.033708 (0.03862) [-0.87285]	0.229645 (0.58452) [0.39288]	0.276218 (0.13838) [1.99609]	0.007179 (0.08577) [0.08370]	0.132057 (0.15612) [0.84585]
D_LOG_OIL(-2)	-0.244543 (0.07991) [-3.06035]	-0.128837 (0.14412) [-0.89399]	-0.037099 (0.03750) [-0.98931]	0.051426 (0.56758) [0.09061]	-0.037865 (0.13437) [-0.28180]	0.025626 (0.08328) [0.30771]	0.192830 (0.15160) [1.27198]
D_LOG_OIL(-3)	0.033467 (0.08787) [0.38088]	0.164750 (0.15847) [1.03960]	0.047350 (0.04124) [1.14827]	0.243843 (0.62413) [0.39069]	-0.002549 (0.14776) [-0.01725]	-0.018534 (0.09158) [-0.20238]	0.092486 (0.16670) [0.55480]
D_LOG_OIL(-4)	0.024413 (0.08576) [0.28468]	-0.123659 (0.15466) [-0.79954]	-0.034081 (0.04024) [-0.84686]	0.268954 (0.60912) [0.44155]	0.198246 (0.14420) [1.37477]	-0.060942 (0.08938) [-0.68185]	0.052521 (0.16269) [0.32282]
D_LOG_OIL(-5)	-0.052648 (0.08497) [-0.61958]	-0.037808 (0.15325) [-0.24670]	-0.068223 (0.03988) [-1.71084]	0.572253 (0.60357) [0.94812]	-0.176183 (0.14289) [-1.23301]	0.007386 (0.08856) [0.08340]	0.076003 (0.16121) [0.47145]
D_LOG_OIL(-6)	0.045761 (0.08450) [0.54154]	0.214396 (0.15240) [1.40680]	-0.008542 (0.03965) [-0.21540]	-0.483777 (0.60020) [-0.80602]	-0.143364 (0.14209) [-1.00895]	0.068460 (0.08807) [0.77735]	-0.173699 (0.16031) [-1.08351]
D_LOG_OIL(-7)	-0.122181 (0.08443) [-1.44717]	-2.07E-06 (0.15227) [-1.4e-05]	0.107508 (0.03962) [2.71342]	-1.007448 (0.59969) [-1.67996]	0.038634 (0.14197) [0.27213]	0.122940 (0.08799) [1.39716]	0.093819 (0.16017) [0.58573]

D_LOG_OIL(-8)	-0.077522 (0.08571) [-0.90443]	-0.054647 (0.15459) [-0.35350]	0.005375 (0.04022) [0.13362]	1.399099 (0.60882) [2.29804]	0.003710 (0.14413) [0.02574]	0.159071 (0.08933) [1.78064]	0.165090 (0.16261) [1.01523]
D_LOG_OIL(-9)	0.051498 (0.08875) [0.58028]	-0.041934 (0.16006) [-0.26199]	0.044223 (0.04165) [1.06183]	-0.479644 (0.63037) [-0.76089]	-0.356072 (0.14923) [-2.38600]	-0.019728 (0.09250) [-0.21328]	-0.001238 (0.16837) [-0.00735]
D_LOG_OIL(-10)	-0.014052 (0.08741) [-0.16076]	0.184434 (0.15764) [1.16996]	-0.057555 (0.04102) [-1.40314]	-0.856715 (0.62085) [-1.37992]	0.107123 (0.14698) [0.72883]	0.103288 (0.09110) [1.13381]	0.160972 (0.16583) [0.97073]
D_LOG_OIL(-11)	-0.177366 (0.08880) [-1.99741]	-0.081442 (0.16015) [-0.50854]	-0.004620 (0.04167) [-0.11087]	0.488410 (0.63073) [0.77436]	0.079533 (0.14932) [0.53264]	0.029679 (0.09255) [0.32068]	0.094638 (0.16847) [0.56177]
D_LOG_OIL(-12)	0.034191 (0.09284) [0.36830]	0.133390 (0.16743) [0.79668]	-0.014742 (0.04357) [-0.33837]	-0.162565 (0.65941) [-0.24653]	-0.069876 (0.15611) [-0.44761]	-0.078947 (0.09676) [-0.81593]	-0.087153 (0.17613) [-0.49483]
D_LOG_OIL(-13)	0.136047 (0.09035) [1.50571]	0.041554 (0.16296) [0.25500]	0.063144 (0.04240) [1.48919]	0.190668 (0.64178) [0.29709]	0.266263 (0.15194) [1.75248]	0.086263 (0.09417) [0.91604]	0.059100 (0.17142) [0.34478]
D_LOG_OIL(-14)	-0.120492 (0.09065) [-1.32922]	0.041422 (0.16349) [0.25336]	0.052090 (0.04254) [1.22448]	0.501042 (0.64388) [0.77817]	0.086499 (0.15243) [0.56746]	-0.078113 (0.09448) [-0.82679]	-0.156953 (0.17198) [-0.91264]
D_LOG_OIL(-15)	-0.226949 (0.08992) [-2.52389]	-0.102411 (0.16217) [-0.63148]	-0.032205 (0.04220) [-0.76319]	-0.158238 (0.63870) [-0.24775]	0.006123 (0.15121) [0.04049]	-0.238916 (0.09372) [-2.54931]	-0.035475 (0.17059) [-0.20795]
D_LOG_OIL(-16)	0.225074 (0.08687) [2.59100]	-0.204787 (0.15667) [-1.30714]	0.049331 (0.04077) [1.21012]	0.544747 (0.61702) [0.88287]	-0.153132 (0.14607) [-1.04833]	0.014707 (0.09054) [0.16244]	0.165376 (0.16480) [1.00348]
D_LOG_OIL(-17)	0.008061 (0.08847) [0.09112]	-0.140771 (0.15955) [-0.88227]	-0.032108 (0.04152) [-0.77337]	-0.081153 (0.62839) [-0.12915]	0.112378 (0.14876) [0.75541]	0.094656 (0.09220) [1.02659]	0.091247 (0.16784) [0.54366]
D_LOG_OIL(-18)	-0.118474 (0.08562) [-1.38366]	-0.205989 (0.15442) [-1.33391]	-0.027013 (0.04018) [-0.67227]	0.038202 (0.60818) [0.06281]	-0.157263 (0.14398) [-1.09225]	0.034902 (0.08924) [0.39111]	0.308987 (0.16244) [1.90213]
D_LOG_GASOLINE(-1)	-0.033278 (0.04305) [-0.77303]	0.042656 (0.07764) [0.54941]	-0.007111 (0.02020) [-0.35201]	-0.030728 (0.30577) [-0.10049]	-0.061260 (0.07239) [-0.84626]	-0.041025 (0.04487) [-0.91437]	-0.073558 (0.08167) [-0.90065]
D_LOG_GASOLINE(-2)	0.090725 (0.04002) [2.26705]	-0.063979 (0.07218) [-0.88643]	0.002059 (0.01878) [0.10962]	-0.083628 (0.28425) [-0.29420]	-0.013223 (0.06729) [-0.19650]	0.052677 (0.04171) [1.26296]	-0.017436 (0.07592) [-0.22965]
D_LOG_GASOLINE(-3)	0.023958 (0.03981) [0.60183]	-0.021494 (0.07179) [-0.29938]	-0.026686 (0.01868) [-1.42850]	-0.389792 (0.28275) [-1.37855]	-0.077043 (0.06694) [-1.15094]	-0.017326 (0.04149) [-0.41760]	-0.056677 (0.07552) [-0.75047]
D_LOG_GASOLINE(-4)	-0.015372 (0.03928) [-0.39132]	0.113218 (0.07085) [1.59808]	0.014916 (0.01843) [0.80912]	-0.138878 (0.27902) [-0.49774]	0.006722 (0.06605) [0.10176]	-0.011311 (0.04094) [-0.27628]	0.076151 (0.07452) [1.02182]
D_LOG_GASOLINE(-5)	-0.046916 (0.03922) [-1.19637]	0.011992 (0.07073) [0.16956]	0.001842 (0.01840) [0.10007]	-0.403404 (0.27854) [-1.44826]	0.080130 (0.06594) [1.21515]	0.036619 (0.04087) [0.89597]	-0.220285 (0.07440) [-2.96090]
D_LOG_GASOLINE(-6)	-0.020177 (0.04127) [-0.48891]	-0.017277 (0.07443) [-0.23212]	0.003189 (0.01937) [0.16466]	0.064426 (0.29313) [0.21978]	0.023664 (0.06940) [0.34099]	-0.031365 (0.04301) [-0.72921]	-0.023476 (0.07830) [-0.29984]
D_LOG_GASOLINE(-7)	0.047678 (0.03906) [1.22061]	-0.069677 (0.07045) [-0.98907]	0.004549 (0.01833) [0.24817]	0.624055 (0.27745) [2.24927]	0.051641 (0.06568) [0.78621]	-0.003399 (0.04071) [-0.08349]	-0.012927 (0.07411) [-0.17444]
D_LOG_GASOLINE(-8)	-0.007341 (0.04051) [-0.18120]	0.025037 (0.07307) [0.34266]	0.016762 (0.01901) [0.88163]	-0.348972 (0.28777) [-1.21269]	-0.050910 (0.06813) [-0.74730]	-0.037033 (0.04222) [-0.87704]	-0.152121 (0.07686) [-1.97916]
D_LOG_GASOLINE(-9)	0.021435 (0.04088) [0.52430]	0.063802 (0.07373) [0.86532]	0.012628 (0.01919) [0.65822]	-0.096411 (0.29038) [-0.33201]	0.054017 (0.06875) [0.78575]	0.031634 (0.04261) [0.74243]	-0.137223 (0.07756) [-1.76923]
D_LOG_GASOLINE(-10)	-0.023012	0.062183	-0.017264	-0.421489	-0.120016	0.022703	-0.077406

	(0.04296) [-0.53571]	(0.07747) [0.80264]	(0.02016) [-0.85638]	(0.30512) [-1.38140]	(0.07223) [-1.66150]	(0.04477) [0.50711]	(0.08150) [-0.94982]
D_LOG_GASOLINE(-11)	0.050042 (0.04364) [1.14679]	-0.005582 (0.07870) [-0.07093]	0.000958 (0.02048) [0.04679]	-0.123410 (0.30995) [-0.39816]	-0.041503 (0.07338) [-0.56561]	0.039824 (0.04548) [0.87564]	-0.086929 (0.08279) [-1.05005]
D_LOG_GASOLINE(-12)	-0.006931 (0.04442) [-0.15601]	0.004543 (0.08012) [0.05670]	0.010937 (0.02063) [0.52461]	0.210179 (0.31555) [0.66608]	0.038862 (0.07470) [0.52022]	0.068517 (0.04630) [1.47982]	-0.067044 (0.08428) [-0.79548]
D_LOG_GASOLINE(-13)	-0.021720 (0.04396) [-0.49406]	0.070891 (0.07929) [0.89409]	-0.052201 (0.02063) [-2.53021]	-0.229531 (0.31227) [-0.73505]	-0.138208 (0.07393) [-1.86955]	-0.092555 (0.04582) [-2.02000]	-0.005200 (0.08341) [-0.06235]
D_LOG_GASOLINE(-14)	0.017950 (0.04686) [0.38305]	0.074551 (0.08452) [0.88208]	0.017114 (0.02199) [0.77822]	-0.280932 (0.33286) [-0.84400]	-0.046537 (0.07880) [-0.59057]	0.106825 (0.04884) [2.18721]	0.060058 (0.08891) [0.67553]
D_LOG_GASOLINE(-15)	0.025469 (0.04873) [0.52264]	-0.001744 (0.08789) [-0.01985]	-0.013660 (0.02287) [-0.59729]	0.051846 (0.34614) [0.14978]	-0.027003 (0.08195) [-0.32952]	-0.012370 (0.05079) [-0.24356]	-0.138448 (0.09245) [-1.49750]
D_LOG_GASOLINE(-16)	-0.069968 (0.04991) [-1.40184]	-0.023351 (0.09002) [-0.25940]	-0.007185 (0.02342) [-0.30677]	-0.483534 (0.35452) [-1.36392]	0.090743 (0.08393) [1.08119]	0.016177 (0.05202) [0.31097]	-0.102686 (0.09469) [-1.08444]
D_LOG_GASOLINE(-17)	-0.063083 (0.04999) [-1.26187]	0.071263 (0.09016) [0.79039]	0.023256 (0.02346) [0.99126]	0.022180 (0.35509) [0.06246]	0.102165 (0.08406) [1.21531]	0.004872 (0.05210) [0.09350]	-0.296011 (0.09484) [-3.12104]
D_LOG_GASOLINE(-18)	-0.045740 (0.04971) [-0.92014]	0.087685 (0.08965) [0.97806]	-0.025139 (0.02333) [-1.07765]	0.091608 (0.35308) [0.25945]	-0.016996 (0.08359) [-0.20333]	-0.145534 (0.05181) [-2.80906]	-0.105721 (0.09431) [-1.12102]
TEMP	-3.13E-05 (6.0E-05) [-0.52135]	2.64E-05 (0.00011) [0.24394]	3.30E-05 (2.8E-05) [1.16896]	0.000597 (0.00043) [1.39977]	1.98E-05 (0.00010) [0.19558]	1.67E-05 (6.3E-05) [0.26714]	-6.17E-05 (0.00011) [-0.54144]
R-squared	0.504780	0.482615	0.490639	0.562480	0.439362	0.481441	0.481114
Adj. R-squared	0.135563	0.096872	0.110880	0.236281	0.021371	0.094823	0.094251
Sum sq. resids	0.039607	0.128830	0.008723	1.998246	0.111994	0.043023	0.142556
S.E. equation	0.015309	0.027610	0.007184	0.108738	0.025743	0.015955	0.029043
F-statistic	1.367164	1.251131	1.291973	1.724348	1.051127	1.245262	1.243631
Log likelihood	900.0232	725.4580	1123.959	319.7115	746.1858	887.7795	710.4748
Akaike AIC	-5.223129	-4.043635	-6.736211	-1.302105	-4.183688	-5.140402	-3.942397
Schwarz SC	-3.639766	-2.460272	-5.152848	0.281259	-2.600324	-3.557038	-2.359034
Mean dependent	-0.001363	0.001882	0.000408	-0.000203	0.000520	0.000286	-0.001002
S.D. dependent	0.016465	0.029053	0.007619	0.124427	0.026022	0.016770	0.030517
Determinant resid covariance (dof adj.)	1.05E-23						
Determinant resid covariance	2.08E-25						
Log likelihood	5471.076						
Akaike information criterion	-30.95997						
Schwarz criterion	-19.87643						