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BEHAVIORAL ASPECTS OF THE EUROPEAN CARBON MARKET

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A mis padres y mi hermana

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Contents

Introduction

1. Behavioral finance

The essays that form this PhD are based on one of the most researched fields nowadays in finance, known as behavioral finance, which proposes psychology and sociology based theories to explain market anomalies. Behavioral finance tries to fill the gap of classical financial models that, based on the idea of fully efficient markets where all the agents interact rationally between each other, are unable to explain mathematically some market behaviors.

More precisely, we are going to focus on four behavioral aspects. The first one is price clustering, which can be defined as the tendency to observe certain trade prices more frequently than others. This fact can affect the decimal part of a number, or the integer, or both. In the absence of market frictions, prices in whatever market should be uniformly distributed across every likely value; however, there is extensive evidence that some prices tend to be traded more frequently than others. The presence of price clustering is considered as a source of market inefficiency due to prices not following a random walk.

The second behavioral aspect analyzed is size clustering, which is defined as the concentration of orders at specific trade sizes. The appearance of this effect that affects the quantity dimension of liquidity can hinder the ability to trade large sizes at low costs. Four different theories appear to explain both price and size clustering. Firstly, the resolution hypothesis indicates that the presence of uncertainty leads the participants to round their equilibrium price and size. Secondly, the attraction hypothesis argues that investors prefer certain numbers to others without any rational explanation. Thirdly, the negotiation hypothesis explains price and size clustering as a matter of convenience, in terms of reducing the costs of negotiation. By using a reduced set of values, the quantity of information that has to be processed by the traders is less and the investor can reach agreements more easily. Finally, the collusion hypothesis suggests that market makers try to negotiate specific prices and trade sizes only to increase the profit margins per transaction.

Another important behavioral basis, also related to the importance that traders give to certain prices above others, is the existence of psychological barriers that create an impediment to an individual's mental outlook, which prevent traders from moving the price of an asset in a certain direction. The financial literature has suggested several possible explanations for the existence of psychological barriers. The first one relates the barriers to the concept of anchoring, which can be defined as the phenomenon whereby individuals fixate on a recent number that may be held out as being important by informed commentators. The second explanation is based on the fact that investors tend to round off arbitrary rational numbers to integers to simplify their trading process. Finally, the third explanation of the psychological barriers effect relates the existence of key prices to the possibility of hedging with options contracts, which implies using pre-established option exercise prices that are usually round numbers.

Finally, the last behavioral aspect that we study is the so-called herding effect. This behavior commonly associated with animals can also be used in finance to define the tendency of investors to mimic the actions of other investors. The existence of this pattern suggests that market participants infer from the previous participants or from the arrival of new information and change their decisions in the direction of the crowd.

Herding behavior can be viewed from two points of view: irrational or rational. The first one, also known as intentional herding, is mainly focused on psychology where people follow one another with the intention of copying the same decisions. Some possible reasons for irrational herding can be the existence of pay-off externalities, principal-agent problems or the existence of informational cascades. This type of behavior can destabilize the market due to massive buys or sells increasing volatility and contributing to bubbles or financial crashes. The second view of herding is the rational or spurious herding that happens when investors react at the same time to certain market conditions or to the arrival of information. This second view is interpreted as a mechanism whereby investors react to the arrival of new public information, which is in line with the Efficient Market Theory.

2. The European Carbon Market

All the questions mentioned above have been studied with regard to the European Union Emissions Trading System (EU ETS), a relatively new market where the investors trading are highly qualified. Due to this fact, we are studying behavioral patterns in a market in which we should not find these types of effects.

The European Carbon Market was set up in January 2005 under Directive 2003/87/EC, when the EU ETS was launched. The EU ETS is a multinational system that covers power generators, heavy industry, energy-intensive industry and aviation emissions of the 28 member countries and the three countries of the European Economic Area –Iceland, Liechtenstein and Norway–, with more than 12,000 installations being subject to the program, covering around 45% of the European Union's greenhouse gas (GHG) emissions. The EU ETS is the largest emissions market in the world both in terms of the volume of emissions traded and the installations covered.

The EU ETS is a cap and trade based system where a limit or cap is fixed to determine the total amount of GHG that can be emitted. This cap is reduced each year and, as a consequence, the total emissions are reduced. Installations participating in the program are subject to monitoring and must report their yearly emissions, and by the 30th of April of the following year each company must surrender enough allowances to cover their emissions, otherwise they will have a non-compliance penalty and heavy fines will be imposed.

Since it was created, the program has been divided into phases: Phase I from 2005 to 2007, Phase II from 2008 to 2012, Phase III from 2013 to 2020 and Phase IV that will take place from 2021 to 2030. The objective of emissions reduction is to emit in 2020 21% less than in 2005. This implies a yearly reduction of 1.74% for Phases I to III and emitting 43% less in 2030, so the yearly reduction will be 2.2% less during Phase IV.

Phase I was known as a pilot period, with the main objective of this phase being to establish a fully-functioning emissions market by the start of the Kyoto Protocol Commitment. In this phase, each member country had to prepare a National Allocation Plan (NAP) that had to be approved by the European Commission. As it was the first phase, countries did not have reliable emissions data and caps were set under best guesses. Penalties were €40 per tonne of CO_2 emitted for which allowances were not surrendered.

Phase II took place at the same time as the Kyoto Protocol Commitment. During this phase, new GHGs were incorporated into the program (nitrous oxide and perfluorocarbons), the number of member countries of the program increased with the joining of the EEA-EFTA states, and the non-compliance penalty was fixed at 100 €/tonne. Another important aspect introduced was the possibility of banking, i.e. the ability to use allowances from the present period in the following one, and borrowing, which is just the opposite, using the allowances from future periods to meet current emissions requirements. Borrowing is allowed only in the same phase and banking is allowed both in the same phase and between phases.

In Phase III, the NAP system was abandoned and from this phase on there will be one single cap for all the member countries. Furthermore, the grandfathering aspect, i.e. the free assignation of emissions allowances to installations, is gradually being reduced. In 2013, more than 40% of the allowances were auctioned. The Commission also focused its efforts on reducing the surplus of emissions from previous phases by implementing short-term measures, such as back-loading, defined as the delay in the auctioning of 900 million allowances from 2014, 2015 and 2016 to be auctioned in 2019 and 2020. In the long term, the Market Stability Reserve (MSR) will be established in 2018, operative from January 2019, which is a rule-based mechanism on the basis of which the auction volumes are adjusted in an "automatic manner" under pre-defined conditions, that reduces the amount of emissions that are auctioned if an upper threshold of emissions in circulation is exceeded, and releases them if the emissions in circulation fall short of a lower threshold.

Also, efforts are being focused on reviewing the free allocation system and to maintain the grandfathering aspect only for those sectors at the highest risk of relocating their production outside the EU, amounting to around 50 sectors. Furthermore, benchmarks will be updated to reflect technological advances since 2008.

The main asset of the European Union Emission Trading System is the Emission Union Allowance (EUA) that grants the owner the right to emit one tonne of CO_2

or equivalent gas. The evolution of the quotation of the EUA has mainly been affected by two events in the first and second phases. During Phase I, the over allocation of allowances and the impossibility of banking to the second phase caused the price of the EUAs for Phase I to sink to zero, and in Phase II this over-allocation problem continued. Furthermore, the financial crisis had an influence on lowering the demand for carbon allowances. Some other events helped to explain the slump in carbon prices in Phase II over 2009 and 2010, such as the wait-and-see attitude of the international negotiations in the Copenhagen summit (December 2009), the failure by allowance sellers to pay back to Member States the VAT they collected (December 2008 to May 2009), and several phishing attacks that hacked into registry accounts (end of 2010). In June 2011, the draft of the European Commission about the Energy Efficiency Directive raised concerns about the (lower) demand for allowances in Phase III, triggering an additional decline in prices. All these events contributed to causing the EUA price to oscillate between €5 and €30 from 2006 to 2015.

3. The ICE ECX

Currently, four platforms offer trading of EU ETS contracts: Nasdaq OMX, Chicago Mercantile Exchange, European Energy Exchange and Intercontinental Exchange (ICE). Among all of them, the ICE market is the most active and concentrates the majority of the volume. The volume originally traded in the European Climate Exchange (ECX) began to be traded in ICE after the purchase of ECX in April 2010. In this platform can be traded the most important futures contracts of the EU ETS whose underlying assets are: EU Allowances (EUAs), EU Aviation Allowances (EUAAs) and Certified Emission Reductions (CERs). It is also possible to trade spot (daily futures) and options contracts. Despite the fact that there are monthly and quarterly maturity contracts, the reference of the market are annual contracts which expire on the last Monday of December.

ICE ECX contracts can be traded for ordinary trades, the Block Trade Facility, for bilateral transactions of large size (minimum 50 lots), or the Exchange of Futures for Physicals (EFP) and Exchange for Swaps (EFS) to transfer an OTC position to an on-exchange futures position.

The ICE Futures Europe market operates an electronic order-driven market with market makers and brokers. The daily session starts with a pre-open period of 15 minutes (from 6:45 a.m. UK local time) to enable market members to input orders in readiness for the beginning of trading. The pre-trading period finishes with a single call auction, where the opening price and the allocated volume are determined by an algorithm. During the continuous session, from 7:00 to 17:00, investors can submit limit orders, market orders, and block orders. The futures market price settlement period runs from 16:50:00 – 16:59:59 UK local time, which is the weighted average during this period. The futures contracts are traded in lots. Each lot equals 1,000 tonnes of CO_2 equivalent, that is, 1,000 EUAs. The minimum tick size was €0.05 until 27 March 2007 when it changed to €0.01. The settlement period for the ICE Futures Contract ceases trading at 17:00 hours UK local time on the last Monday of the contract month.

ICE ECX is a price driven market where trades submitted are listed in a unique Limited Order Book and are executed following a price and time criteria. This Limited Order Book is open during the continuous session for transparency purposes but the orders entered and the executed trades are anonymous.

4. Dissertation structure

The PhD dissertation is structured in four different chapters. The aim of the dissertation is to study some behavioral aspects in the European Carbon Market, focusing on the European Union Allowance futures, which is the main asset of this market. Specifically, the four objectives are: (i) to assess the existence of price clustering, (ii) to test the presence of size clustering and its relationship with price clustering, (iii) to study the existence of psychological barriers on prices and volatility, and (iv) to investigate the presence of herding behavior among carbon traders.

The titles of the chapters that form the PhD dissertation are:

- Chapter I: Assessing price clustering in the European Carbon Market.
- Chapter II: What makes carbon traders cluster their orders?
- Chapter III: Do price barriers exist in the European Carbon Market?
- Chapter IV: Do carbon traders behave as a herd?

Chapter I studies the presence of price clustering in the European emission market. Its existence is inconsistent with economic rationality and it is not in agreement with the idea that prices follow a random walk. In this chapter we find a strong presence of price clustering at prices ended in 0 and 5, supporting both the attraction hypothesis and the negotiation hypothesis.

Chapter II documents size-clustering behavior in the European Carbon Futures Market and analyzes the circumstances under which it happens. Our findings show that carbon trades are concentrated in sizes of 1 to 5 contracts and in multiples of 5. We have also shown that more clustered prices have more clustered sizes, suggesting that price and size resolution in the European Carbon

Market are complementary and that carbon traders round both the price and the size of their orders.

Chapter III investigates the existence of key reference points in the European Carbon Market. We document the presence of key levels and barrier bands around European Union Allowances (EUAs) prices and we show that traders tend to consider these price levels as resistances in upward movements and as supports in downward movements. Furthermore, we have observed that the existence of price barriers affects both return and volume dynamics.

Finally, Chapter IV detects the existence of the herding effect in the European Carbon Futures Market. Preliminary tests prove the presence of herding at high frequency data. A pattern analysis shows that herding intensifies with the level of speculation and other behavioral bases such as psychological prices or price clustering. Finally, we observe that herding behavior destabilizes the market due to the overreaction of volatility to past herding behavior.

5. The Data

The entire PhD dissertation is based on the study of Emission Union Allowances (EUAs). As we have mentioned previously, this asset can be traded in different markets such as spot, options or futures. However, the European Carbon Market is characterized by the low relevance of options and spot markets and, by far, the major concentration of EUAs in terms of volume can be found in the December maturity. For these reasons, we have chosen the EUA futures contract with December maturity traded in ICE ECX as the reference benchmark, given that this platform concentrates the highest activity among all the platforms that trade EUAs.

The database is composed of two types of data: daily and intraday data, and for both we have December futures contracts from 2005 to 2020. Intraday series contain the time stamp, the trade price, the size and the sign of the transaction, i.e. whether it is buyer or seller initiated. In addition, the options intraday database used contains the strike price. On the other hand, the daily data contains open, close, high and low prices, the total volume and the open interest. All the prices are nominated in euros, the time stamp is measured in GMT and the volume and open interest are in lots.

More precisely, in Chapter I we use both intraday and daily data of EUA futures contracts with maturity in 2010. This contract goes from 21 September 2006 to 20 December 2010 over which time 304,189 transactions took place. This futures series belongs to Phase II but it started to be traded during Phase I, so we can compare if there is any difference in the period in which the futures contract is traded, either the Phase I period or the Phase II period.

Chapter II includes three different maturities, December 2010, 2011 and 2012, which allows us to examine the results obtained over the years. The data sample periods run from 21 September 2006 to 20 December 2010, from 23 March 2006 to 19 December 2011, and from 23 March 2006 to 17 December 2012, for the December 2010, 2011 and 2012 futures contracts, respectively, covering in this way the whole lifespan of the three December futures contracts. A total of 304,189, 359,003 and 491,205 transactions took place, for the first, second and third futures contracts analyzed, respectively.

The sample period analyzed in Chapter III takes the December front contract of Phase II that goes from 18 December 2007 to 17 December 2012. Three different databases have been employed by us in this chapter: futures daily data and intraday data for futures and options. The sample contains 1,306,765 transactions for a total trading volume of 9,201,096 futures contracts and the price oscillates between €5.61 and €29.69. The most repeated price is €15.25. The majority of the transactions have a size of 1 lot and the maximum number of futures contracts traded in one transaction was 1,682.

Finally, Chapter IV uses intraday and daily data for EUA futures with maturity during Phase III. More precisely, the December futures maturities that contain the front contract are 2013, 2014 and 2015. During the period from 18 December 2012 to 14 December 2015, 1,214,304 transactions took place.

6. Summary of the chapters

The thesis dissertation has covered different aspects of behavioral finance applied to the European Carbon Market. Chapter I starts with the study of price clustering in the EUA futures market; Chapter II extends the analysis to size clustering and its relation to price clustering; Chapter III tests the influence of key prices in the behavior of EUA returns, volatility and volume; and Chapter IV detects the existence of herding behavior in the European Carbon Market.

Chapter I: Assessing price clustering in the European Carbon Market. The presence of price clustering in markets is taken as a sign of market inefficiency that can influence trading strategies. In this chapter, we study the presence of a concentration in prices in carbon futures markets. Specifically, we analyze the European Carbon Futures Market and test for evidence of a preference for certain prices above others. Our results reveal the strong presence of price clustering in the carbon market at prices ending in digits 0 and 5. These findings support the attraction hypothesis, which endorses a significant clustering on gravitational prices, but also backs the negotiation hypothesis, which advocates greater clustering when trading costs are higher.

A first version of this chapter was written during the last year of my Quantitative Finance Master's degree. The first version of the chapter was presented at the IX Workshop in Banking and Quantitative Finance (Toledo, Spain, July 2011), organized by the University of Castilla La Mancha. The final version was submitted in July 2011 and it was accepted in October 2011 by *Applied Energy*.

Chapter II: What makes carbon traders cluster their orders? The ability to trade large amounts of assets at low costs could be hindered when the size of the orders is concentrated at specific trade sizes. This chapter documents evidence of size clustering behavior in the European Carbon Futures Market and analyzes the circumstances under which it happens. Our findings show that carbon trades are concentrated in sizes of one to five contracts and in multiples of five. We have also demonstrated that more clustered prices have more clustered sizes, suggesting that price and size resolution in the European Carbon Market are complementary and that carbon traders round both the price and the size of their orders. Finally, the analysis of the key determinants of the size clustering reveals that traders use a reduced number of different trade sizes when uncertainty is high, market liquidity is poor, and the desire to open new positions and cancel old ones is very strong.

A first version of this chapter was written during the last year of my Quantitative Finance Master's degree. The first version of the chapter was presented at the IX Workshop in Banking and Quantitative Finance (Toledo, Spain, July 2011), organized by the University of Castilla La Mancha. The preliminary version was accepted for presentation at the VIII Conference of the Spanish Association for

Energy Economics (Valencia, Spain, January 2013). A preliminary version of this paper was published by Instituto Valenciano de Investigaciones Económicas (IVIE) as Working Paper (WP-EC 2012-10). The final version was submitted to *Energy Economics* in October 2013, and it was finally accepted in March 2014.

Chapter III: Do price barriers exist in the European Carbon Market? It is generally thought that psychological prices in markets primarily traded by professional participants should play a limited role. This chapter investigates the existence of key reference points in the European Carbon Market, which can be considered as a market with highly qualified stakeholders. We document the presence of key levels and barrier bands around European Union Allowances (EUA) prices. It appears that traders tend to consider these price levels as resistances in upward movements and as supports in downward movements. Furthermore, we have observed that the existence of price barriers affects both return and volume dynamics.

A preliminary version of this paper was presented at the XIV Iberian-Italian Congress of Financial and Actuarial Mathematics (Madrid, Spain, January 2013), at the X Spanish Association for Energy Economics (Tenerife, Spain, January 2015), and at the 6th Workshop on Energy Markets (Valencia, Spain, March 2015). The final version was submitted to *The Journal of Behavioral Finance* in December 2015, and it was finally accepted in June 2016.

Chapter IV: Do carbon traders behave as a herd? This chapter analyzes the presence of herding behavior in the European Carbon Futures Market. It is important to remember that this is a blind market in which the vast majority of investors are institutional. Both features lead us to study the existence of herding under very restrictive conditions. An intraday trade database has been used in order to analyze this phenomenon at high frequencies. A pattern analysis shows that herding intensifies with the level of speculation and other behavioral biases like psychological prices or price clustering. The reaction of seller-initiated trades to the arrival of market news also induces an increase in the degree of herding. Furthermore, we detect higher levels of herding with higher levels of uncertainty and with a larger number of trades. Finally, we show that herding destabilizes the market and leads traders to overreact to these circumstances.

A preliminary version of this paper was presented at the XVI Iberian-Italian Congress of Financial and Actuarial Mathematics (Paestum, Italy, May 2016). The final version was submitted to *The North American Journal of Economics and Finance* in September 2016.

7. Stays, grants and prizes

I developed my PhD dissertation thesis in the University of Valencia (Department of Financial Economics, Valencia, Spain), as a PhD student from the University.

During my PhD I have participated in different workshops:

- Introducing this PhD dissertation at *Jornadas de seguimiento de tesis Doctorales,* (Bilbao), 19 December 2014.
- Presenting the study entitled *Do price barriers exist in the European Carbon Market?* at the 6th research workshop on energy markets (Valencia), 27 March 2015.
- Discussing the study entitled *European natural gas seasonal effects on futures hedging* at the 6th research workshop on energy markets (Valencia), 27 March 2015.

- Discussing the study entitled *A new look at oil price pass-through into inflation: Evidence from disaggregated European data* at the 7th research workshop on energy markets (Valencia), 11 March 2016.

The research was financially supported by:

- A Mobility Grant for official master's degree from the Ministry of Education (Spain), during the master's degree period.
- The Spanish Ministry of Economy and Competitiveness through the researching project Quantitative Finance (ECO2013-40816-P).
- The contribution of the Department of Middle Office of Repsol Trading to introduce a chapter of this dissertation in a workshop.

Chapter I

ASSESSING PRICE CLUSTERING IN EUROPEAN CARBON MARKETS

1. Introduction

Price clustering can be defined as the tendency to observe certain trade prices more frequently than others. This effect can affect the decimal part of a number or the integer or both. In the absence of market frictions, prices in whatever market should be uniformly distributed across every likely value. However, there is extensive evidence that some prices tend to be traded more frequently than others. The presence of this stylized fact is considered as a source of market inefficiency.

Since Niederhoffer (1965) and Osborne (1962) observed this fact in the New York Stock Exchange, a large number of studies have documented it in a wide range of assets.[1] Four different theories appear to explain price clustering well. Firstly, the price resolution hypothesis, introduced by Ball, Torous and Tschoegl (1985), indicates that the presence of uncertainly leads the participants to round their equilibrium price. The higher the uncertainty, the higher the market volatility and the higher the probability of finding price clustering. Secondly, the attraction hypothesis argues that investors prefer certain numbers than other without any rational explanation. This particular preference for certain numbers above others can create some level of clustering. Although there are different versions of the attraction theory, all the authors agree when they refer to the decreasing order of the frequencies of the more observed last digits of the prices: transaction prices ending in zero are stronger attracters than prices ending in digit 5, which are stronger than the rest of prices. Furthermore, the sum of frequencies of prices

[1] To date, Narayan, Narayan and Popp (2001) is the only reference that has studied price clustering in energy markets. Specifically, they consider five different oil types and for each oil type they analyze four different contracts. The rest of the empirical literature investigates price clustering in financial assets. See Brown and Mitchell (2008) for an excellent survey of this kind of literature.

around the most gravitational points (0 and 5), that is those trade prices ending in 1, 9, 4 and 6 should be greater than the sum of the frequencies of observations of prices ending in 8, 2, 7 and 3 (see, for example Goodhart and Curcio (1991), Loomes (1988) and Mitchell (2001)). Thirdly, the negotiation hypothesis developed by Harris (1991) states price clustering as a matter of convenience, in terms of reducing the costs of negotiation. By using a reduced set of prices, the quantity of information that has to be processed by the traders is less and the investor can reach agreements more easily. Assuming this point of view, a coarser grid occurs because traders use a restricted set of prices to simplify their negotiations. Therefore, the higher the market volatility and the less the trading frequency, the higher the trading costs and the higher the level of clustering. Finally, the price collusion hypothesis proposed by Christie and Schultz (1994) suggests that market makers would try to negotiate specific prices only to increase the profits margins per transaction.

Following Narayan et al. (2001), the rationale of studying price clustering is that its presence is inconsistent with economic rationality and it is not in agreement with the idea that prices follow a random walk.[2] Furthermore, Schwartz, Van Ness and Van Ness (2004) reveals that price clustering may be of interest to traders because (i) investors who are aware of clustering points may be able to trade at slightly better prices and may be able to place limit orders higher in time/price priority by avoiding the clustering points; and because (ii) clustering can be interpreted as a signal that traders assign relevant information to some specific prices.

[2] Feng, Zou and Wei (2011) show that carbon price is not a random walk and, as a consequence, the price history information is not fully reflected in current carbon price.

The goal of this chapter is to document evidence of price clustering behavior in the ECX European Union Allowances (EUA) futures market taking into account intraday transactions data. The behavior of the EUA price is crucial for European Climate Policy, and the investigation of clustering in EUA prices can provide new insights into the efficiency of the European Carbon Future Markets.[3] In fact, as far as we know, this study pioneers the investigation of clustering in carbon futures market. Besides examining price clustering, we study the factors that can explain such clustering. The chapter proceeds as follows. Section 2 briefly explains the European Carbon Market and the data used to perform this study. Section 3 describes the methodology. Section 4 discusses the findings on price clustering, and Section 5 summarizes and concludes.

2. Market structure and data

The European Union Emissions Trading Scheme (EU ETS) was launched in January 2005 and is the world's largest carbon trading system. Established under Directive 2003/87/ EC, the EU ETS limits the carbon dioxide emissions from European installations that include power generation, mineral oil refineries, offshore installations, and other heavy industrial sectors. Under the EU ETS, each Member State must surrender annually to the European Commission a National Allocation Plan which sets out that Member State's total quantity of emission allowances (known as European Union Allowances, or EUAs) to be allocated to all installations covered by the EU ETS in that Member State and how those

[3] See Zhang and Wei (2010) for an excellent summary of the main arguments of empirical studies on the EU ETS.

emissions allowances will be distributed to each installation which holds a permit to emit carbon dioxide.[4]

The EU ETS is run on a cap-and-trade basis, i.e., emissions from each installation are capped and therefore if an installation emits below this level, then it will be able to trade its excess of EUAs. One EUA represents the right to emit one metric ton of carbon dioxide equivalent. At this moment, it is possible to trade EUAs in spot, futures and options electronic platforms. Four European electronic markets currently offer trading EUAs: European Climate Exchange (ECX), BlueNext, European Energy Exchange (EEX), and Nord Pool. Among all of them, the ECX EUA Futures Market is by far the most active and liquid.

The ECX market operates an electronic order-driven market with market makers and brokers. The daily session starts with a pre-open period of 15 minutes (from 6:45 a.m. UK local time) to enable market members to input orders in readiness for the beginning of trading. The pre-trading period finishes with a single call auction, where the opening price and the allocated volume are determined by an algorithm. During the continuous session, from 7:00 to 17:00, investors can submit limit orders, market orders, and block orders. The future contracts are traded in lots. Each lot equals 1,000 tonnes of CO_2 equivalent, that is, 1,000 EUAs. The minimum tick size was €0.05 until 27 March 2007 when it changed to €0.01. The settlement period for the ECX Futures Market runs from 16:50:00 – 16:59:59 UK local time for the purpose of determining the settlement price, which

[4] The EU ETS has been organized in two Phases. Phase 1 ran from 2005 to 2007, and Phase 2 that runs from 2008 to 2012 and coincides with the Kyoto Commitment Period. It is supposed that further phases will follow in the future. See Mansanet-Bataller and Pardo (2008) for further details about the European Union Emissions Trading Scheme.

is the weighted average during this period. Futures Contract ceases trading at 17:00 hours UK local time on the last Monday of the contract month.[5]

To perform this study, we have chosen the ECX EUA futures contracts with maturity in December 2010. This contract began to be traded on 21 September 2006, and, until its maturity on 20 December 2010, 304,189 transactions took place. Therefore, until now, the December 2010 ECX EUA futures contracts is the expired futures contract with the longest record of trading data. Specifically, for every screen trade, our database reports: the time stamp measured in GMT, the traded price in Euros, the maturity of the contract, the traded volume, the sign of the transaction (buyer or seller initiated) and the daily settlement price.

3. Methodology

Basic statistical analysis has been carried out to establish the presence and the profile of price clustering in carbon futures markets. Following Ikenberry and Weston (2007), we have applied the Hirshmann-Herfindahl index (*HHI*) to measure price clustering. This index is commonly used to analyze market power, but in this case is applied to test the concentration in prices and how it varies from a uniform distribution. The *HHI* is calculated by summing the squared values of the market shares of all market participants. In our case, we substitute shares of markets participants for percentages of all trades that occur at all available digits. Specifically:

$$HHI = \sum_{i=1}^{N} (f_i)^2$$

[5] For further details on the EUAs future contracts, see the user guide of ECX Contracts at the www.theice.com.

where f_i is the frequency of trades that occur at fraction *i*, *i* = 1, 2,.., *N* possible ticks. The *HHI* is computed based upon the last digit of the trade price according to the minimum tick. If there was no price clustering, *HHI* should be equal to 100/*N*.

To test the statistical significance of price clustering in one sample, we have calculated the frequency of trades based on the last digit of the transaction price. If the Theory of Efficient Markets holds, the observed frequency of all the available digits of the last decimal number of price will be the same, i. e. we assume a uniform distribution of the frequency of the digits. To test this fact, we use the standard Chi-square goodness-of-fit statistic whose null hypothesis (H1 hypothesis, from now on) is the absence of difference between the observed distribution and the expected distribution:

$$D = \sum_{i=1}^{N} \frac{(O_i - E_i)^2}{E_i}$$

where O_i is the observed frequency of the last digit; E_i is the expected frequency under uniform distribution, and *D* is the distributed Chi-square with *N-1* degrees of freedom under standard conditions. A large value of *D* would signify a significant deviation from uniform distribution and would imply significant price clustering.

When clustering is detected, it can be of interest to check if the level of price clustering is the same for two different samples. In this case, the following statistic will be calculated:

$$\widetilde{D} = \left(\frac{D_2}{D_1}\right) \sim F_{N_2-1,N_1-1}$$

where D_i follows a standard Chi-square distribution with *N-1* degrees of freedom and the ratio follows an F-Snedecor distribution with N_2*-1* and N_1*-1* degrees of freedom. In this case, the underlying null hypothesis (H2 hypothesis, from now on) to be tested is if the two samples considered are equality clustered.

To perform a comparison among two proportions of two different samples, the z-test will be used. The null hypothesis of this test assumes that there is no difference between the proportions in both samples. The expression of the statistic is as follows:

$$Z = \frac{p_1 - p_2}{s_{p_1 - p_2}} \; where: s_{p_1 - p_2} = \sqrt{\hat{p}\,\hat{q}}\sqrt{\frac{n_1 + n_2}{n_1 n_2}}$$

$$\hat{p} = \frac{n_1 p_1 + n_2 p_2}{n_1 + n_2} \; and \; \hat{q} = 1 - \hat{p}$$

where p_1 and n_1 (p_2 and n_2) are the proportion and the number of observations of sample 1 (sample 2).

Finally, based on previous empirical works, a multivariate analysis will be carried out in order to determine the key factors which drive clustering in carbon prices. Specifically, the following model has been estimated using both ordinary least squares and the Newey and West correction that accounts for heteroskedasticity and serial correlation:

$$Price\ Clustering_t = \alpha + \beta_1 \sigma_t + \beta_2 Trading\ Frequency_t + \beta_3 Trade\ Size_t + \beta_4 R3_{H,t} + \beta_5 R3_{L,t} + \epsilon_t$$

The intraday volatility (σ_t) has been calculated following the measure proposed by Parkinson (1980):

$$\sigma_t = \sqrt{\frac{1}{4log2}(logH_t - logL_t)^2}$$

where H_t is the highest and L_t are the lowest traded prices on day *t*. Volatility is widely considered as a proxy for uncertainty, therefore the greater the volatility, the greater should be the level of price clustering. *Trading frequency* is defined as the number of trades per day. This variable is commonly associated with efficiency in price determination; the greater the *Trading frequency*, the greater is the liquidity, prices are known more precisely, and the extent of price clustering should be less. *Trade size* is computed as the daily average trade size calculated as the quotient of the sum of the total amount of the transactions expressed in Euros divided by the number of transactions. Large size orders are sometimes associated with informed agents (see Easly and O'Hara (1987)) and their placement should lead to greater clustering. However, ap Gwilym, Clare and Thomas (1988, p.1197) indicate that for larger trades market participants may find it worthwhile negotiating on a wider range of prices. Finally, we have taken into account the daily ratio proposed by Lucia and Pardo (2010) and defined as the quotient between the daily change in the open interest and the daily trading volume. This ratio oscillates between -1 and 1. When the ratio takes values close to 1 and -1, it means that traders are massively opening and closing positions, respectively. Specifically, we have introduced the dummy variable $R3_H$ that takes the value 1 on those days in which the ratio takes values between 0.95 and 1 and zero otherwise, and $R3_L$ that takes the value 1 on those days in which the ratio takes values between -1 and -0.95 and zero otherwise.

4. Price clustering results

4.1. Univariate analysis

In this section, we perform different tests in order to check clustering in carbon transaction prices. We examine all trade prices with a tick size of one cent. We use the last digit of the price of all intraday screen transactions of the December 2010 ECX EUA futures contract to summarize clustering. Before testing for the existence of price clustering, we have divided the sample of five years into two periods: 2006-2007 and 2008-2010. The reason is twofold: (i) the number of observations for the first period (413 obs.) is by far very small in comparison to the number of observations for the second period (303,776 obs.), and (ii) the results are clearly affected by the change in tick from €0.05 to €0.01 in March 2007.

Table 1 shows the frequency distribution of the last digit of trade prices for the two periods. We find clear evidence of clustering in both periods, being more notorious in the first one. Panel A presents the carbon pricing grid and indicates a high concentration of prices ending in digits 0 and 5 for both periods. The percentage of trades that occur at the most frequently used prices (x.x0 and x.x5) is 66.8% (=41.9%+24.9%) and 31.21% (=16.24%+14.97%), for the first and second period, respectively. Panel B confirms the presence of price concentration in both periods. The H1 indicates the rejection of the null hypothesis of the absence of difference between the observed distribution and the expected distribution for each subperiod. The *HHI* values show a higher price concentration in the first period (25.42) than in the second one (10.81). The test of the H2 hypothesis, not reported in the paper, confirms statistically this difference at the 1% level. There is an obvious explanation to this great difference, namely that until March 2007, all the transaction prices ended in 0 or 5 because the minimum fluctuation tick was €0.05. This is the reason why the rest of the analysis is going to be focused exclusively on the second period. Specifically, if we focused on transactions in years 2008, 2009 and 2010, we observe that the sum of frequencies of observations of prices ending in 1, 9, 4 and 6 (33.11%) is less than the sum of frequencies of prices ending in 8, 2, 7 and 3 (35.60%). The z-test statistic for comparing such proportions is 11.97, indicating that such difference is statistically significant at the 1% level, giving support to the attraction hypothesis as a plausible explanation for the detected profile in carbon price clustering.

Table 2 shows the evolution of the price clustering through the three years of the second period. It can be observed that clustering is persistent through time but it decreases every year. There are several items that indicate this fact. The level of the clustering at the 0 and 5 digits decreases from 51.7% (=28.5%+23.2%) in 2008 to 30.3% (=15.7%+14.6%) in 2010. This fact can also be observed in the *HHI* that decreases from 16.47 to 10.69. Therefore, as the futures contract moves toward its expiration in 2010, the degree of price clustering is smaller. This behavior suggests that clustering will be affected by the time to maturity and it would confirm the hypothesis suggested by Ball et al. (1985) that price clustering should diminish as futures contracts move toward expiration, because the price of the underlying asset is better known. However, another possible explanation for this effect could be found in the increment of the trading frequency observed for each year. The higher the trading frequency is, the less is the degree of price clustering. This last phenomenon was employed by Harris (1991) to argue his negotiation hypothesis.

Once we have detected clear evidence of significant clustering on carbon market prices, the next question to be solved is in which situations is the clustering more notorious. For this purpose, we have measured the clustering in several scenarios. We have studied the price clustering in the maximum and minimum prices trading during the day, in the price of the last transaction of the day, and in the daily settlement price of the futures contract. Furthermore, we also analyze if price clustering is influenced by the sign of the trade, i.e., whether the trade is buyer initiated or seller initiated. Finally, we have taken into account the daily ratio proposed by Lucia and Pardo (2010) to differentiate between days in which traders have opened or closed massively their positions.

Table 3 presents the results for all the scenarios considered. We observe that there is clustering for the highest, the lowest, and for the price of the last transaction, with *HHIs* of 11.11, 11.38 and 11.05, respectively. The clustering is statistically significant in all the cases at the 1% level. The picture is totally different in the case of the grid of prices for the daily settlement prices. While the prices of the last transaction prices show a clear clustering in digits 0 and 5 (32.27%=16.62%+15.55%), the settlement price frequencies do not present price clustering. The *HHI* is 10.13 and the null hypothesis of absence of clustering (H1) cannot be rejected. This is an interesting finding given that the settlement price is used in many papers as the reference for the price in carbon market and the results show that this price series is the only one in which a coarser grid of prices is not detected. The explanation for this result could be found in the fact the settlement price is a trade weighted average.

Next, we have divided the sample of intraday transactions prices taking into account the sign of the order. The price concentration is significant at the 1% level in both samples. We cannot reject the null hypothesis of equality of the price clustering (H2) between buyer and seller initiated trades (the p-value is 0.62).

Finally, we have tested if there is a coarser grid when the trading session is dominated by traders that are closing or opening positions massively. We observe that traders cluster on prices ending in 5 (29.31%) when they are massively opening carbon futures positions contracts. However, when they are closing positions, the most repeated digits turn out to be 0 and 5, with 12.79% and 18.25%, respectively. In both cases, the null hypothesis of the absence of price clustering is rejected at the 1% level. Notice that, in spite of the high value of the *HHI* for days with high *R3* values (17.43), the hypothesis of equality in price clustering between the two subsamples (H2) cannot be rejected.

4.2. Multivariate analysis

Taking into account the results obtained in the univariate analysis, we define the measure *Price clustering* as the sum of the percentages that occur at pricing increments of x.x0 and x.x5 on day *t*. Furthermore, given that *Trading Frequency* and *Trade Size* variables are highly positive skewed, we report multivariate results for the natural logarithm of such variables.[6]

Table 4 shows the Spearman cross-correlation coefficients among *Volatility, Frequency Trading* and *Trade Size*, all of them described in section II, and the *Price Clustering* variable. We observed that frequency of clustering is, positively and significantly correlated with the measure of volatility at the 10% level, but negatively and significantly correlated with the number of trades per day at the 1% level. Surprisingly, we do not observe any relationship between *Price Clustering* and the *Trade Size* variable.

[6] These tests are not included for the sake of brevity, but are available from the authors upon request.

Next, we have performed a multivariate regression analysis in order to detect the key determinants of the price clustering in the carbon market. Following Schwartz et al. (2004), given that the measure of price clustering is limited between 0% and 100%, we use the inverse of the standard normal cumulative distribution as our measure of price clustering for regression purposes. Specifically, we regress *Price Clustering* against daily volatility, the logarithm of daily trading frequency, the logarithm of daily trade size and $R3_H$ ($R3_L$) defined as a dummy variable that takes value 1 when *R3* is between 0.95 and 1 (-1 and -0.95) and zero otherwise.

Table 5 presents the results of the multivariate regression analysis. We find that *volatility* and *Trade Size* influence positively and significantly price clustering at the 5% and 10% level, respectively. On the contrary, *Trading Frequency* has the opposite effect and affects it negatively at the 1% level of significance. Therefore, our findings indicate that price clustering in the European Carbon Markets increases when surrogates for greater uncertainty such as volatility and trade size rise. However, the degree of price clustering is lower when liquidity increases; that is, it decreases with trading frequency. As a whole, these results suggest that a coarser pricing grid occurs because traders want to make their negotiations less costly. These results appear to support the negotiation hypothesis proposed by Harris (1991) as the most plausible explanation for the price clustering detected in the European Carbon Futures Markets.

5. Conclusions

The results obtained for price clustering highlight the existence of this fact in the European Carbon Futures Markets. In particular, we have detected that prices are concentrated in transaction prices ending in digits 0 and 5, and that the level of price clustering is higher at prices of x.x0 than at prices of x.x5.

The knowledge that carbon price clustering exists is relevant for several reasons. Firstly, it is important from the point of view of the microeconomics of carbon price formation since the degree of rounding may be used as a new proxy in studies to take into account the amount of information present in the carbon market. Secondly, clustering in prices is not in agreement with the idea that prices follow a random walk and, as a consequence, carbon risk managers should dedicate further effort to finding alternative models that consider clustering in order to price and hedge EUAs. Finally, knowing of the existence of carbon pricing clustering, profitable trading rules can be implemented by carbon traders. These strategies should be based on the assumption that a reversal in the direction of the price of the EUA becomes likely as the price moves to some gravitational price. For example, if trades are taking place at €14.99, sellers may be able to trade at slightly better prices by placing limit orders at €15.00 in order to get priority in time, while buyers can submit market orders in order to gain priority in prices.

Preferences for the carbon prices ending in 0 and 5 give initial support to the attraction hypothesis as a possible explanation for the price clustering. However, the extent of price clustering is greater when less information is available in the market, that is, when the volatility is high and the trading frequency is low. It seems that price clustering occurs because traders use a restricted set of prices to simplify their negotiations. These results point to the negotiation hypothesis proposed by Harris (1991) as the most plausible explanation for the concentration in prices observed in the European Carbon Market.

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Annex: tables and figures

Table 1. Price Clustering in ECX EUA futures contracts

Panel A: Distribution of last digit of the price

	2006-2007		2008-2010	
Pricing Grid	Number	%	Number	%
x.x0	173	41.90%	49319	16.24%
x.x1	16	3.87%	23601	7.70%
x.x2	17	4.12%	26592	8.75%
x.x3	33	7.99%	26197	8.62%
x.x4	9	2.18%	26047	8.57%
x.x5	103	24.90%	45490	14.97%
x.x6	24	5.81%	26049	8.57%
x.x7	17	4.12%	27359	9.01%
x.x8	8	1.94%	28013	9.22%
x.x9	13	3.15%	25109	8.27%
Total	413		303776	
% at x.x0 & x.x5		66.80%		31.21%

Panel B: Clustering tests and indices

	2006-2007	2008-2010
H1	0.0000	0.0000
HHI(%)	25.42	10.81

Note: Panel A shows the number of transactions and the percentage of ECX EUA futures contracts with maturity in December 2010 traded at the 1 cent interval for period 2006-2007 and period 2008-2010. Panel B presents the p-value of the H1 hypothesis that tests the absence of difference between the observed distribution and the expected distribution. *HHI* stands for the Hirshmann-Herfindahl index.

Table 2. Price Clustering for 2008, 2009 and 2010

Panel A: Distribution of last digit of the price

Pricing Grid	2008	2009	2010
x.x0	28.50%	18.70%	15.70%
x.x1	5.23%	7.84%	7.80%
x.x2	5.21%	8.55%	8.84%
x.x3	5.56%	7.79%	8.79%
x.x4	6.71%	7.27%	8.79%
x.x5	23.20%	16.40%	14.60%
x.x6	6.41%	7.77%	8.73%
x.x7	5.46%	8.46%	9.14%
x.x8	7.88%	8.66%	9.32%
x.x9	5.88%	8.53%	8.26%
Total	3996	38026	261754
% at x.x0 & x.x5	51.70%	35.10%	30.30%

Panel B: Clustering tests and indices

	2008	2009	2010
H1	0.0000	0.0000	0.0000
HHI(%)	16.47	11.50	10.69

Note: Panel A shows the number of transactions and the percentage of ECX EUA futures contracts with maturity in December 2010 traded at the 1 cent interval for trading years 2008, 2009 and 2010. Panel B presents the p-value of the H1 hypothesis that tests the absence of difference between the observed distribution and the expected distribution. *HHI* stands for the Hirshmann-Herfindahl index.

Table 3. Analysis of scenarios for price clustering

Partition	**x.x0**	**x.x1**	**x.x2**	**x.x3**	**x.x4**	**x.x5**	**x.x6**	**x.x7**	**x.x8**	**x.x9**	**Observations**	*HHI*	**H1**	**H2**
All trades	16.24	7.77	8.75	8.62	8.57	14.97	8.58	9.01	9.22	8.27	303776	10.81	0.0000	-
High	17.43	9.12	8.85	8.85	9.65	15.28	6.57	6.97	8.58	8.71	746	11.11	0.0000	-
Low	16.22	7.91	8.58	9.38	7.64	18.23	7.51	6.84	9.38	8.31	746	11.38	0.0000	0.6242
Last	16.62	9.38	7.37	10.99	7.77	15.55	7.10	7.77	8.18	9.25	746	11.05	0.0000	-
Settle	11.53	11.39	10.59	9.79	10.32	10.72	8.98	10.32	8.04	8.31	746	10.13	0.3677	0.0024
Buyer	15.67	9.13	9.32	8.50	7.67	15.14	9.64	9.20	8.80	6.93	149558	10.79	0.0000	-
Seller	16.78	6.45	8.21	8.74	9.45	14.82	7.54	8.82	9.63	9.56	154218	10.95	0.0000	0.6206
$R3_H$	6.34	3.32	3.32	6.34	12.08	29.31	19.94	15.11	2.72	1.51	331	17.43	0.0000	-
$R3_L$	12.79	7.26	8.70	7.74	7.62	18.25	8.70	12.36	9.18	7.38	1666	11.10	0.0000	0.3366

Note: This table shows the percentage of cases clustered at the final digit of transaction price for various partitions of the sample for period 2008-2010. We examine clustering for all the trades of the period, the highest, the lowest, the last, and the settlement price of each day. We also study the degree of price clustering depending on the sign of the transaction, i.e. (trade that is buyer or seller initiated) and attending to whether traders have opened ($R3_H$) or closed ($R3_L$) positions in futures contracts massively along the day. *HHI* stands for the Hirshmann-Herfindahl index. H1 presents the p-value of the statistic that tests the null hypothesis of absence of price clustering. H2 presents the p-value of the statistic that tests if the two samples considered are equally clustered.

Table 4. Spearman cross-correlation coefficients

	Price Clustering	σ	Trading Frequency
σ	0.0633 (0.0840)	1.0000	
Trading Frequency	-0.1792 (0.0000)	0.4326 (0.0000)	1.0000
Trade Size	0.0236 (0.5198)	-0.4327 (0.0000)	-0.1776 (0.0000)

Note: This table shows the Spearman cross-correlation coefficients of price clustering (the sum of the percentages of trades at x.x0 and x.x5), the measure of volatility proposed by Parkinson (1980), the trading frequency (logarithm of daily number of transactions) and trade size (logarithm of the sum of the product of price and volume divided by the daily trading frequency) for the December 2010 ECX EUA futures contracts and for the period 2008-2010. P-values appear in parentheses.

Table 5. Determinants of price clustering

Variable	Coefficient	Std. Error	t-statistic	p-value
α	-0.4097	0.2472	-1.6573	0.0979
σ_t	6.2181	2.5268	2.4608	0.0141
Trading Frequency$_t$	-0.0833	0.0113	-7.3602	0.0000
Trade Size$_t$	0.0852	0.0464	1.8359	0.0668
$R3_{H,t}$	-0.2632	0.1797	-1.4649	0.1434
$R3_{L,t}$	0.1293	0.1110	1.1647	0.2446
R^2	0.1220	F-statistic		19.3154
Adjusted R^2	0.1156	Prob(F-statistic)		0.0000

Note: Price clustering is measured as the inverse of the standard normal cumulative distribution of the percentage of trades that occur at pricing increments of x.x0 and x.x5. We regress Price Clustering against daily volatility, the logarithm of daily trading frequency, the logarithm of daily trade size and $R3_H$ and $R3_L$ dummy's variables which take value 1 when *R3* is in the intervals [0.95 1] and [-1 -0.95], respectively. The analysis has been performed for the December 2010 ECX EUA futures contracts and for the period 2008-2010.

Chapter II

WHAT MAKES CARBON TRADERS CLUSTER THEIR ORDERS?

1. Introduction

Since the inception of the European Union Emission Trading Scheme (EU ETS) in 2005, an increasing number of empirical papers have studied the microstructure of the European Carbon Market. Benz and Hengelbrock (2008) were the first to study market liquidity in carbon markets and observe that trading frictions in the form of transaction costs decreased over the first years of the EU ETS; Mansanet-Bataller and Pardo (2009) and Conrad, Rittler and Rotfuß. (2012) show that the decisions of the European Commission have a strong and immediate impact on carbon prices; Mizrach and Otsubo (2014) find that imbalances in the order book of the European Climate Exchange (ECX) help predict carbon returns for up to three days; and Medina, Pardo and Pascual (2014) analyze the timeline of trading frictions in the European Carbon Market to conclude that the EU ETS market breakdown in 2006 had a persistent negative effect on the quality of the EUAs prices.[7]

Although the previous papers have studied a broad range of topics about carbon market liquidity, none of them have focused on the quantity dimension of liquidity. This is an important aspect to consider when trading. Following Meng, Verousis and ap. Gwilym (2013), to the extent that investors fail to accommodate size along with price in their optimal allocation decisions, their overall costs may increase. As Black (1971, p.30) indicates, an asset is perfectly liquid when (i) there are always bid and ask prices for the investor who wants to trade small amounts of assets and the difference between those prices is always small; (ii) an investor can trade a large amount of the asset over a long period of time at a

[7] See Zhang and Wei (2010) for a comprehensive review of the main arguments of empirical studies on the EU ETS, in terms of the operating mechanism and economic effect of the EU ETS.

price not very different from the current market price; and (iii) an investor can buy or sell a large block of stock immediately, but at a premium or discount that depends on the size of the block. According to Harris (2003, p. 399), a trader must minimize the cost of trading a given size or, similarly, maximize the size she trades at a given cost. However, the ability to trade large sizes at low costs could be hindered when the size of the orders is concentrated at specific trade sizes. This empirical fact, known in the literature as the size clustering effect, has recently been observed in foreign exchange, equity, index futures, and credit default swap (CDS) markets (see Alexander and Peterson, 2007; ap Gwilym and Meng (2010); Meng et al., (2013); Moulton, (2005), respectively).

The financial literature offers some theories to explain clustering. Firstly, the price negotiation hypothesis, introduced by Ball, Torous and Tschoel (1985) and by Harris (1991), indicates that the presence of uncertainly leads the traders to round both trade sizes and their equilibrium prices, with the aim of minimizing the costs of the trading process. Secondly, there are some papers that suggest that the tendency to round sizes and prices is due to trader's preferences. This is the case of different behavioral hypotheses suggested by Wyckoff (1963), Goodhart and Curcio (1991), and Ikenberry and Weston (2007), among others, that argue that investors prefer certain numbers over others without any rational explanation. By using a rounded set of numbers, the quantity of information that has to be processed by the traders is less. Combining these hypotheses, clustering appears because traders use a restricted set of prices and trade sizes to simplify their negotiations. Therefore, the higher the market volatility and the less the trading frequency, the higher the trading costs and the higher the level of clustering.

Finally, Hodrick and Moulton (2009) examine liquidity and how it affects the behavior of uninformed traders. One of the implications of their model states that in a market with many heterogeneous uninformed investors, the number of different sizes traded increases in accordance with their desire for satisfaction. If the desire for satisfaction is very high, they choose to trade a wide range of different sizes. Therefore, the degree of size clustering should be very low at times in which the desire of portfolio managers to satisfy their negotiations is very intense. [8]

The finding of coarse price grids, or price clustering, is common across a broad range of markets, including, among others, energy, water, foreign exchange, stock, bond futures, stock index futures, and carbon futures markets. However, as we have cited, the literature about the presence of size clustering is far less extensive.[9] This study offers the first analysis of observed patterns in European Union Allowances (EUAs) trade sizes. Specifically, the purpose of this paper is to document empirical evidence of size clustering behavior in the ECX EUA futures market and to understand under what circumstances it happens. The investigation of clustering in trade sizes could offer new insights into the liquidity of the European Carbon Futures Markets as long as its presence would be indicative of the fact that carbon traders might not negotiate their desired quantities at a given price. As we will show in this paper, size and price rounding will result in lower transactions costs. Additionally, the results of this study

[8] Moulton (2005) analyzes size clustering in the foreign exchange market and shows that customers trade more precise quantities at quarter-ends because this is when investors could have a stronger desire to satisfy their quantity demands. A similar explanation is provided by Garvey and Wu (2014) to justify why US equity traders submit more non-rounded order sizes and more order sizes overall leading up to a day's market close.

[9] See Brooks et al. (2013) and ap Gwilym and Meng (2010) for excellent reviews of the literature on price and size clustering, respectively.

contribute to the debate by providing further empirical evidence on whether price and size clustering are coincident or not.

The remainder of the chpater is organized as follows. Section 2 describes briefly the European Carbon Market and the data used to perform this study. Section 3 analyzes the distribution of the trade sizes. Section 4 presents the findings on size clustering and its key determinants. Section 5 summarizes and concludes.

2. Market structure and data

Next, we provide a brief description about the main characteristics of the EU ETS. For further information, see Ellerman et al. (2010) for a detailed explanation of the origins and development of the EU ETS, and Ellerman et al. (2014) for a descriptive analysis of the history and structure of the EU ETS from its inception through 2012.

The EU ETS was launched in January 2005 and is, at the moment, the first international emission trading system to address greenhouse gas emissions from companies. The EU ETS covers emissions from power plants, factories and companies belonging to energy-intensive industry sectors in the 28 EU countries and the three European Economic Area states (Iceland, Liechtenstein and Norway). Flights to and from the EU and the three European Economic Area states are also covered. These installations and flights represent around 45% of the EU's greenhouse gas emissions.

The EU ETS has evolved from a system with 25 national caps and decentralized allocation based on national allocation plans dealing with CO_2 emissions alone towards a centralized system that includes several greenhouse gases (GHGs) and features an EU-wide cap (see Ellerman et al., 2014). Within this cap, companies may receive or buy emission allowances each year. These allowances give the holder the right to emit 1 tonne of CO_2 and are known as European Union Allowances, or EUAs. If a company considers that it has more allowances than it is going to need, it can sell them in the market. However, each company must surrender enough allowances to cover all its emissions for the previous year by the 30th of April of the following year, otherwise heavy fines are imposed.

The EU ETS is organized in Phases. Pilot Phase I ran from 2005 to 2007. The number of allowances allocated was so high that the EUA price fell to zero in 2007. Phase II ran from 2008 to 2012 and coincided with the Kyoto Commitment Period. The cap was lowered by 6.5% with regard to the level in the previous period. However, the economic crisis again caused an unexpected surplus of allowances. Phase III, spanning 2013 to 2020, will cover new industries and has a prolonged compliance cycle. It will incorporate a centralized EU-wide allocation of allowances with a yearly linear decrease of the emissions cap of 1.74% per year, even beyond 2020. During Phases I and II the majority of the allowances were allocated freely. From 2013 on, there is a combination of free allocation and auctioning, and the ETS legislation has set the goal of phasing out free allocation completely by 2027.[10]

Several electronic trading platforms currently offer trading on EUAs. However, the ICE ECX EUA Futures Market is considered as the benchmark as it concentrates by far the majority of the total trading volume. In fact, following the Futures Industry Association, the ICE ECX EUA Futures contract is among the

[10] See ec.europa.eu/clima/policies/ets/index_en.htm for further details about the European Union Emissions Trading Scheme (last accessed on December 30, 2014).

top 20 most-traded Energy Futures & Options Contracts in the world.[11] The ICE ECX market is an electronic order driven market whose daily session commences with a pre-open period of 15 min (from 6:45 a.m. UK local time) and ends with a single call auction. Throughout the continuous session, from 7:00 to 17:00, brokers and market makers are able to submit limit orders, stop limit orders, market orders, and block orders. The futures contracts are traded in lots, with each lot equaling 1000 tonnes of CO_2 equivalent, in other words, 1000 EUAs. The minimum tick size was €0.05 until 27 March 2007 when it changed to €0.01. Futures contracts cease trading at 17:00 h UK local time on the last Monday of the contract month.[12]

To carry out this study, we have chosen the complete lifespan of the ECX EUA futures contracts with maturities in December 2010, 2011 and 2012, all of them belonging to Phase II. The data sample periods run from 21 September 2006 to 20 December 2010, from 23 March 2006 to 19 December 2011, and from 23 March 2006 to 17 December 2012, for the December 2010, 2011 and 2012 futures contracts, respectively. A total of 304,189, 359,003 and 491,205 transactions took place, for the first, second and third contracts analyzed, respectively.

Specifically, our database contains, for every screen trade, the following concrete information: the time stamp measured in GMT, the traded price in euros, the contract maturity date, the traded volume, the daily settlement price, and the sign of the transaction specifying whether it is buyer- or seller-initiated. Following

[11] See http://www.futuresindustry.org/volume-.asp for trading volume statistics on Global Futures and Options (last accessed on September 30,2013).
[12] For further details on the EUAs futures contract, see the user guide of ECX Contracts at www.theice.com (last accessed on September 26, 2013).

Alexander and Peterson (2007), a trade that has been buyer-initiated is more likely to be followed by another buyer-initiated order if the trades are rounded. Therefore, we will take into account the sign of the transaction to check if trades initiated by one of the sides could be more size clustered than trades initiated by the other side.

3. Trade size distribution

In this section, we begin by using the data on trade sizes to calculate their frequency. Table 1 shows the frequency of the trades with the same trade size expressed in percentage for all the trades (All trades), for buyer-initiated trades (Buyer), and for seller-initiated trades (Seller) for the ECX EUA futures contracts with maturities in December 2010, 2011 and 2012. The empirical distribution shows that about 68% of the trades are concentrated in sizes of one to five contracts in all the maturities. We also observe spikes at size multiples of five with an upturn at trades of 25 contracts. Furthermore, both buyer- and seller-initiated trades seem to be distributed in a similar way in the three futures contracts.

Table 2 presents the basic descriptive statistics. The average trade size for the sample of all the transactions ranges between 7.6 and 8.6, the minimum transaction size is one and the maximum is 1682 contracts (2012 December futures contract). However, the median is three, which gives an idea of the high concentration of trades around the lowest sizes. These results are in line with those obtained by ap Gwilym and Meng (2010) for the FTSE100 futures contract. They suggest that this tendency to concentrate on small sizes could be the desire of traders to avoid trading large orders with a better-informed counterparty.

From Table 1, there appear to be little difference in the pattern of trade sizes between buyer- and seller-initiated trades. Next, we have formally tested the equality of means, medians and variances of both distributions with the parametric Anova F-test, the non-parametric Kruskal–Wallis test and the Brown–Forsythe's test, respectively. Additionally, we have applied the Wilcoxon/Mann–Whitney test, a nonparametric test based on ranks, which determines whether or not two groups have the same general distribution.

The results are displayed in Table 2. The null hypotheses of equality of means, medians and variances cannot be rejected for the maturity in 2010. However, they are rejected at the 1% level for the 2011 and 2012 futures contracts. Furthermore, the non-parametric Wilcoxon/Mann– Whitney statistics for those contracts confirm that the distribution of the buyer-initiated trade sizes is statistically different from the distribution of the seller-initiated trade sizes at the 1% level. Therefore, the results of all these tests indicate that the distributions of trade sizes are affected by the sign of the order, at least for the last two maturities.

Following Alexander and Peterson (2007), in order to formally test if the degree of size clustering in all the samples is significant, we conduct a linear regression analysis:

$$\begin{aligned} \ln Perc.Size_i = \alpha_i + \beta_5 D5_i + \beta_{10} D10_i + \beta_{15} D15_i + \beta_{20} D20_i \\ + \beta_{25} D25_i + \beta_{upper\ 25} DM5_i + \beta_{Ln\ Size,i} LnSize_i + \varepsilon_i \end{aligned}$$

where the dependent variable is the natural log of the percentage of trades that occur at size *i* and we include as independent variables some dummy variables that will capture whether the trade size sample is affected by the round numbers. In particular, as about 95% percent of trade sizes occur in the range defined between one and twenty-five contracts, we include the dummy variables that will detect if the trade size is equal to 5, 10, 15, 20 or 25 contracts. In addition, we adapt from Blau, Van Ness and Van Ness (2012) the variable DM5 which identifies trade sizes which are multiples of five and bigger than twenty-five. Finally, to check how the level of size clustering is affected by the size of the transaction, we include the variable $LnSize_i$ which is the natural logarithm of trade size i measured in number of contracts.

Table 3 shows the results of the round trade sizes regression analysis carried out using both ordinary least squares and the Newey and West correction that accounts for heteroskedasticity and serial correlation problems. In all the cases, the adjusted-R^2 is higher than 96% and all the coefficients are statistically significant at the 1% level. For all the maturities and for the three subsamples, the dummy variables that check the trade size are positively related with the dependent variable, as we expected from Table 1. Regarding the variable $LnSize_i$, we find that its coefficient is negative and significant, meaning that the larger the size of the transaction the lower the frequency of trades with such size.

4. Size clustering

4.1. Univariate analysis

Previous empirical evidence has caused controversy regarding whether price and size clustering are complementary or substitutes. Alexander and Peterson (2007) and Verousis and ap Gwilym (2013) find that price and size clustering tend to occur simultaneously in stock markets. On the contrary, studies such as ap Gwilym and Meng (2010) for FTSE100 index futures markets, Blau et al. (2012) for NYSE short sales, and Meng et al. (2013) for the CDS market, observe that when traders round prices they tend to quote more refined sizes, implying a trade-off between price and size clustering. Given that Palao and Pardo (2012) show the existence of price clustering in December 2010 ECX EUA futures contract at prices ending in digits 0 or 5, we have also tested for its presence in the December 2011 and 2012 futures contracts. The idea is to study possible links between price and size clustering and to determine whether they are complementary or substitutes in the European Carbon Market.

First of all, to investigate the presence of price clustering, we focus on the distribution of the last decimal of the transaction price, in particular, the frequency distribution of prices between x.x0 and x.x9. We analyze price clustering as the frequency of the number of transactions occurring at each digit (%Trades) and, following Brooks, Harris and Joymungul (2013), we have also studied price clustering as the frequency of the total amount of contracts traded at each digit (%Contracts).

Price clustering has been analyzed for the sample of all the transactions, for buyer-initiated trades and for seller-initiated trades. Table 4 shows that the most clustered digits for the three subsamples of each contract are 0 and 5. This fact is observed both in the number of trades and in the total amount of contracts. It is notable that when we take into account the frequency of the total amount of contracts traded, the percentage observed for trade prices at x.x0 and x.x5 is higher than when we consider the total number of trades. Obviously, the opposite is detected for the remaining digits. This suggests that investors not only trade more frequently at digits 0 and 5 but also, when they trade at these digits, they place a higher amount of contracts than in the rest of the cases.

Additionally, we have applied the Goodness of Fit Chi-squared statistic to test the null hypothesis of no difference between the observed distribution and the expected distribution. The Goodness of Fit Chisquared statistic, shown in Panel B as GOF, is defined as:

$$GOF = \sum_{i=1}^{n} \frac{(O_i - E_i)^2}{E_i} \sim \chi^2_{N-1}$$

where O_i is the observed frequency of the last digit; E_i is the expected frequency under a uniform distribution, and GOF is the distributed Chi-square with *N-1* degrees of freedom under standard conditions. In all the cases, the tests reject the null hypothesis at the 1% level, confirming statistically the presence of price clustering both in the number of trades and in the sum of contracts at prices ending in digits 0 and 5.

Next, we define different variables and perform different tests in order to check for the presence of size clustering in carbon markets. We follow the methodology proposed both by Moulton (2005) and by ap Gwilym and Meng (2010). Specifically, we define the variable *Size* as the daily number of different trade sizes; *Count* as the daily trading frequency, and *Volume* as the daily volume. A simulated example of the daily trading activity in a fictitious market in Table 5 will help to clarify these variables. Panel A presents all the intraday trades for two consecutive days. Panel B shows how these trades are classified according to different subsamples. In our case, we perform the analysis for the full sample and two subsamples that takes into account prices that end in digit 0, in digit 5, in digits 0 or 5, and in digits different from 0 or 5. Finally, Panel C shows the percentages for each subsample.

For example, for Day 1 there are three transactions recorded (see Panel A), the variable *Count* indicates three transactions, while two trades of size one and one trade of size ten constitute two *Sizes* on the same day (see Panel B). Panel C deserves special attention because the proportion of size one (2/5) is bigger in the sample of prices ended in 0 than in the whole sample (3/10) as happens for size one. It is explained because, for each sample, we only consider the sum of the different sizes corresponding to each sample. The full sample has ten trades while the subsample of digit-0 has five. For this reason, additively cannot be assumed when comparing the different samples of *Size*.

The reason for employing the daily number of distinct trade sizes (the variable size) instead of the variable trade sizes to measure the degree of size clustering is because we are interested in analyzing the amplitude of the range of the trade sizes and not the frequency of the observations for each trade size. Proceeding in this way, we avoid the possibility that a trading day with a high number of trades could determine the size clustering level. For instance, we do not mind if the trade size quantity equal to one repeats 20 times, though we do mind if an investor can trade at such quantity. Therefore, a high (low) number for the variable Size implies a low (high) degree of size clustering.

Next, we perform different tests in order to check size clustering in carbon trades. We examine all trade sizes of all intraday screen transactions of the three futures contracts and we calculate the daily variable Size. Table 6 presents some descriptive statistics and some tests for the different samples considered. Panel A shows that the median of the daily number of different trade sizes for the sample of All trades is lower for prices ending in 0 or 5 than for prices ending in digits different from 0 or 5. Similar results are obtained for Buyer and Seller subsamples. The Kruskal–Wallis (K–W) test in Panel A confirms that this difference is statistically significant at the 1% level in all cases. Therefore, more clustered prices have more clustered sizes, indicating that price and size clustering are complementary. Panel B presents the Wilcoxon/Mann– Whitney statistics and their p-values that test the null hypothesis of equality of the distributions for the Buyer and Seller subsamples. As can be observed, we cannot reject the equality of the distributions of the variable size between the buyer-initiated trades and the seller initiated trades in any of the cases. Therefore, the sign of the order affects the trade size of the order (as we see in Table 2) but it does not influence the variable size. This is the reason why, from now on, the multivariate analysis will be focused only on the sample composed of all the transactions.

4.2. Multivariate analysis

Finally, based on previous empirical evidence obtained for other assets, a multivariate analysis is carried out to determine the key factors which affect size clustering in carbon prices. To study possible links between price and size clustering, and following ap Gwilym and Meng (2010), we have split the data set into two parts in order to capture any differences between observations with prices ending in x.x0 and x.x5 and those with prices ending in the remaining digits. To do this, we have defined D_t as a dummy variable that takes the value 1 for observations where prices end in digits different from 0 or 5, and 0 otherwise. Observations are indexed by t where t = 1,698 across 849 trading days for 2010 futures contract, t = 2,032 across 1,016 trading days for 2011 maturity, and t = 2,670 across 1,335 trading days for 2012 futures contract.

The following model has been estimated using both ordinary least squares and the Newey and West correction that accounts for heteroskedasticity and serial correlation problems:

$$
\begin{aligned}
Size_t = \alpha_t + \beta_1 \sigma_t + \beta_2 Count_t + \beta_3 Trade\,Size_t + \beta_4 R3_{H,t} + \beta_5 R3_{M,t} \\
+ \beta_6 R3_{L,t} + \beta_7 D_t + \beta_8 D_t \sigma_t + \beta_9 D_t Count_t \\
+ \beta_{10} D_t Trade\,Size_t \quad + \beta_{11} D_t R3_{H,t} + \beta_{12} D_t R3_{M,t} \\
+ \beta_{13} D_t R3_{L,t} + \epsilon_t
\end{aligned}
$$

The dependent variable that represents the level of size clustering is the variable *Size*$_t$ which refers to the daily number of distinct trade sizes. σ_t stands for an estimation of the intraday volatility that has been calculated following the measure proposed by Parkinson (1980):

$$
\sigma_t = \sqrt{\frac{1}{4log2}(logH_t - logL_t)^2}
$$

where H_t is the highest and L_t are the lowest traded prices on day t. We will use volatility as a proxy of uncertainty. According to Harris (1991), the arrival of more information implies more volatility and a wider range of trade sizes. Moulton (2005) observes higher volatility associated with more sizes traded in the majority of the currencies she analyzed and Meng et al. (2013) also observe this relationship for the CDS market.

Therefore, the coefficient on σ_t is expected to be negative in the equation. *Count*$_t$ is the number of daily trades for each sample. ap Gwilym and Meng (2010) find that the number of distinct trade sizes increases with trade frequency which is consistent with the idea that the arrival of more information leads to the use of a wider range of trade sizes. Therefore, the expected sign for the coefficient on *Count*$_t$ is positive, i.e. the more trades there are, the greater the number of distinct trade sizes. *Trade* $Size_t$ is calculated as the daily average trade size, i.e. the sum of the total amount of trade sizes divided by the number of the total transactions on such day. As we have seen, our preliminary results suggest that the average trade size is higher for the most clustered prices, and by introducing this variable into the regression, we can test whether the daily average trade size influences the range of the different trade sizes.

Finally, motivated by the theoretical paper by Hodrick and Moulton (2009), we have introduced three dummy variables. Their paper examines liquidity and how it affects the behavior of portfolio managers. One of the implications of their model is that in a market with many heterogeneous uninformed investors, an asset will trade at more distinct quantities when investors have a stronger desire to satisfy their exogenous demands, where “at more distinct quantities” refers to more variation in the quantities ($Size_t$) traded, not necessarily more trades or more total volume. Assuming the correctness of this theory, the degree of size clustering on days with extreme desire would be negatively linked with the desire of uninformed investors (portfolio managers) to satisfy their negotiations.

We apply the $R3_t$ measure proposed by Lucia and Pardo (2010) as a proxy to study the behavior of the portfolio manager activity in the European Carbon Market. This measure is defined as the ratio between the change in the open interest and the daily trading volume over a day *t*. The ratio has no dimension, and can take any value ranging from −1 to +1. A positive (negative) number indicates that the number of open (closed) positions is greater than the number of closed (open) positions. After calculating the ratio for all the trading days, we have constructed three variables. $R3_{H,t}$, $R3_{M,t}$ and $R3_{L,t}$ which take value 1 when $R3_t$ is in the intervals [0.95, 1], [−0.025, 0.025] and [−1, −0.95], respectively. The first dummy variable indicates days in which the opening of new positions outnumbers by far the closing of positions; the second variable identifies those days with an abnormal number of intraday traders (those that open and close positions on the same day), while the last variable takes into account days in which the traders are massively closing positions.

The results of the regression analysis are presented in Table 7 and show a high explanatory power, given that the adjusted-R^2 is at least 76%. After controlling for all the possible determinants of size clustering, the dummy variable for prices ending in digits different from 0 or 5 is positive and statistically different from zero at the 1% level, indicating that there are higher distinct trade sizes for prices ending in digits different from 0 or 5 than for prices ending in 0 or 5. This implies that more clustered prices have a lower range of distinct sizes, and therefore, more clustered sizes. This suggests that price and size clustering take place at the same time.

We find that volatility does not affect the size variable for the less clustered prices in any contract and is only negatively related with the dependent variable in the case of more clustered prices for the 2011 maturity at the 5% level, which means that when uncertainty increases, investors prefer to trade transactions ending in 0 or 5 at a small range of sizes. We also observe a positive and significant relationship between the daily number of transactions and the daily number of distinct trade sizes that is not counterbalanced for prices ending in digits different from 0 or 5. Regarding the relationship between average trade size and size clustering, the results indicate that when it is significantly different form zero, it is negative. Therefore, the higher the daily average trade size, the lower the range of the different trade sizes. The overall result of these findings supports both the price negotiation and the behavioral hypotheses.

Finally, it is important to note the results obtained when we observe how size clustering behaves under different investor decision scenarios. The coefficients of the dummy variables that represent massive opening positions ($R3_{H,t}$) and massive closing positions ($R3_{L,t}$) are negative at the 1% level for more clustered prices. Similar results are obtained for significant coefficients of the interaction variables. This means that carbon traders concentrate the size of their trades on days in which they open new positions and on days in which they cancel the old ones, but on those days that intraday carbon traders are extremely active ($R3_{M,t}$) they prefer to use a wide range of trade sizes. Therefore, this result backs the theory by Hodrick and Moulton (2009) which states that, in a market with many heterogeneous uninformed investors, the number of different sizes traded increases with their desire for satisfaction.

5. Conclusions

This study investigates, for the first time, the presence and the key determinants of the size clustering in the ICE ECX EUA futures market taking into account intraday transactions data. We have found evidence of a tendency for carbon trades to cluster in small sizes and in round numbers multiples of five contracts. We have also demonstrated that more clustered prices have more clustered sizes, implying that price and size resolution in the European Carbon Market are coincident and that carbon traders place orders rounding the two variables simultaneously. This suggests that market players not only trade more frequently at transaction prices ending in digits 0 or 5 but also, when they trade at these digits, they place a lower number of different trade sizes than in the remaining cases. Furthermore, the analysis of the key determinants of trade size clustering indicates that carbon traders cluster their orders to simplify their trading process when uncertainty is high, market liquidity is poor, and the desire to open new positions or cancel old ones is very strong. We interpret all these findings as being supportive of both the price negotiation and the behavioral hypotheses.

Our findings indicate that there was a reduction in the extent of price and size clustering over the final years of Phase II for transaction prices ending in digits different from 0 or 5. However, the existence and persistence of a high degree of size clustering in transaction prices ending in digits 0 or 5 hinders the ability of traders to negotiate orders with large sizes at low costs. These results should be of great interest for carbon market players inasmuch as the concentration of the size of trades at certain amounts in the European Carbon Market implies that carbon market participants may not be able to trade the desired quantity easily. Moreover, our overall findings suggest that carbon traders that want to transact large trades should seek out liquidity peaks, namely, they should round the price of their orders to digits ending in 0 or 5 and, simultaneously, either adjust the size of their trades to make them smaller or in multiples of five contracts.

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Annex: tables and figures

Table 1. Frequency of the trades with the same trade size

	2010			2011			2012		
	All trades	Buyer	Seller	All trades	Buyer	Seller	All trades	Buyer	Seller
1	42.82	42.82	42.83	41.05	40.15	41.92	39.41	40.42	38.35
2	6.94	7.12	6.77	8.19	8.29	8.09	9.17	9.04	9.31
3	4.05	4.08	4.03	4.96	4.95	4.97	5.65	5.45	5.86
4	3.16	3.19	3.13	3.25	3.36	3.14	3.47	3.49	3.45
5	11.14	11.11	11.16	10.88	11.00	10.76	10.49	9.90	11.12
6	1.25	1.23	1.26	1.33	1.39	1.27	1.52	1.55	1.49
7	1.24	1.23	1.24	1.39	1.41	1.37	1.49	1.49	1.48
8	1.24	1.22	1.27	1.17	1.23	1.10	1.29	1.32	1.26
9	1.47	1.42	1.52	1.26	1.29	1.23	1.30	1.31	1.28
10	10.28	10.17	10.38	8.22	8.25	8.19	8.41	8.21	8.62
11	0.42	0.43	0.40	0.65	0.65	0.66	0.53	0.51	0.54
12	0.39	0.39	0.40	0.46	0.47	0.45	0.57	0.58	0.55
13	0.37	0.38	0.37	0.41	0.45	0.37	0.45	0.47	0.43
14	0.39	0.41	0.38	0.44	0.47	0.41	0.44	0.45	0.43
15	1.42	1.46	1.39	1.51	1.57	1.46	1.44	1.48	1.40
16	0.29	0.28	0.30	0.33	0.34	0.33	0.33	0.36	0.31
17	0.29	0.29	0.29	0.32	0.34	0.31	0.32	0.32	0.32
18	0.27	0.26	0.28	0.31	0.32	0.30	0.36	0.37	0.35
19	0.35	0.37	0.34	0.37	0.39	0.35	0.35	0.38	0.32
20	1.70	1.66	1.74	1.65	1.71	1.58	1.64	1.65	1.64
21	0.24	0.24	0.23	0.26	0.28	0.23	0.25	0.25	0.24
22	0.27	0.28	0.25	0.30	0.30	0.31	0.28	0.30	0.25
23	0.36	0.39	0.32	0.34	0.35	0.33	0.31	0.34	0.29
24	0.59	0.60	0.57	0.51	0.52	0.51	0.43	0.45	0.41
25	5.43	5.40	5.46	5.83	5.93	5.72	5.01	5.00	5.01
>25	3.63	3.55	3.71	4.61	4.58	4.64	5.10	4.93	5.28

Note. This table shows the frequency of the trades with the same trade size expressed in percentage for all the trades (*All trades*), for buyer-initiated trades (*Buyer*), and for seller-initiated trades (*Seller*) for the ECX EUA futures contracts with maturities in December 2010, 2011 and 2012. The first column indicates the number of contracts per transaction.

Table 2. Descriptive statistics of trade sizes

Panel A. 2010

	All trades	Buyer	Seller	Test
Mean	7.612	7.587	7.636	F- test: 0.7623
Median	3	3	3	KW- test: 1.749
Std. Deviation	15.543	15.577	15.510	BF- test: 0.617
Minimum	1	1	1	WMW- test: 1.323
Maximum	995	976	995	
Observations	304,180	149,737	154,443	

Panel B. 2011

	All trades	Buyer	Seller	Test
Mean	8.285	8.466	8.112	F- test: 36.322***
Median	3	3	2	KW- test: 89.164***
Std. Deviation	17.612	18.652	16.556	BF- test: 25.304***
Minimum	1	1	1	WMW- test: 9.443***
Maximum	900	900	518	
Observations	359,003	175,490	183,513	

Panel C. 2012

	All trades	Buyer	Seller	Test
Mean	8.610	8.428	8.800	F- test: 40.153***
Median	3	3	3	KW- test: 113.812***
Std. Deviation	20.559	20.076	21.051	BF- test: 26.653***
Minimum	1	1	1	WMW- test: 10.668***
Maximum	1682	1493	1682	
Observations	491,205	251,562	239,643	

Note. This table shows the descriptive statistics of the distribution of trade sizes for all the trades (*All trades*), for buyer-initiated trades (*Buyer*), and seller-initiated trades (*Seller*) for the ECX EUA futures contracts with maturities in December 2010, 2011 and 2012. The sample period takes into account all the transactions made from 2006 to 2012. The *F*-test stands for the *F* statistic that tests the null hypothesis of equality of means of trade sizes. The *KW*-test is the Kruskal-Wallis statistic that tests the null hypothesis of equality of medians of trade sizes. The *BF*-test is the Brown–Forsythe's statistic that tests the null hypothesis of equality of variances. The *WMW*-test is the Wilcoxon/Mann–Whitney statistic that tests whether or not two series have the same general distribution. ***, ** and * indicate significance at 1%, 5% and 10%, respectively.

Table 3. Round numbers analysis regression

Panel A. 2010

	All trades	Buyer	Seller
α	3.679	3.678	3.677
β_5	1.597	1.586	1.602
β_{10}	2.751	2.728	2.764
β_{15}	1.495	1.502	1.477
β_{20}	2.186	2.144	2.214
β_{25}	3.745	3.721	3.754
$\beta_{upper\ 25}$	2.328	2.265	2.380
β_{LnSize}	-1.780	-1.774	-1.781
Adjusted-R^2	0.961	0.962	0.960

Panel B. 2011

	All trades	Buyer	Seller
α	3.656	3.635	3.674
β_5	1.544	1.538	1.543
β_{10}	2.475	2.447	2.492
β_{15}	1.492	1.487	1.483
β_{20}	2.079	2.070	2.071
β_{25}	3.733	3.698	3.751
$\beta_{upper\ 25}$	2.489	2.396	2.568
β_{LnSize}	-1.748	-1.725	-1.765
Adjusted-R^2	0.965	0.966	0.965

Panel C. 2012

	All trades	Buyer	Seller
α	3.641	3.656	3.622
β_5	1.482	1.406	1.552
β_{10}	2.454	2.411	2.488
β_{15}	1.388	1.396	1.365
β_{20}	2.017	1.997	2.022
β_{25}	3.514	3.492	3.521
$\beta_{upper\ 25}$	2.425	2.343	2.494
β_{LnSize}	-1.722	-1.721	-1.718
Adjusted-R^2	0.968	0.969	0.968

Note. This table shows the results of a regression analysis (equation 1) in order to test how round numbers affect trade sizes for all the trades (*All trades*), for buyer-initiated trades (*Buyer*), and seller-initiated trades (*Seller*) for the ECX EUA futures contracts with maturities in December 2010, 2011 and 2012. $LnPerc.Size_i$ is the natural logarithm of the percentage of trade size *i*. $D5_i$, $D10_i$, $D15_i$, $D20_i$ and $D25_i$ are five dummy variables which take value 1 if the trade sizes *i* are equal to 5, 10, 15, 20 and 25, respectively, and 0 otherwise. $DM5_i$ takes value 1 if the trade sizes i is a multiple of 5 upper *25* and 0 otherwise. $LnSize_i$ is the natural logarithm of trade size i measured in number of contracts. All the coefficients are significant at the 1% level.

Table 4. Price clustering

Panel A. 2010

	All sample		Buyer		Seller	
	% Trades	% Contracts	% Trades	% Contracts	% Trades	% Contracts
x.x0 & x.x5	31.26	37.71	30.85	37.34	31.65	38.07
Rest	68.74	62.29	69.15	62.66	68.35	61.93
Total	304,180	2,315,306	149,737	1,136,001	154,443	1,179,305
GOF	24,756.67	464,341.74	11,928.42	221,485.43	14,731.21	256,690.75
p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Panel B. 2011

	All sample		Buyer		Seller	
	% Trades	% Contracts	% Trades	% Contracts	% Trades	% Contracts
x.x0 & x.x5	28.61	34.19	28.02	33.24	29.17	35.14
Rest	71.39	65.81	71.98	66.76	70.83	64.86
Total	359,003	2,974,379	175,490	1,485,744	183,513	1,488,635
GOF	17,378.67	393,079.03	7771.34	174,284.79	10,724.64	231,185.30
p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Panel C. 2012

	All sample		Buyer		Seller	
	% Trades	% Contracts	% Trades	% Contracts	% Trades	% Contracts
x.x0 & x.x5	28.51	31.67	28.41	31.86	28.62	31.48
Rest	71.49	68.33	71.59	68.14	71.38	68.52
Total	491,205	4,229,186	251,562	2,120,267	239,643	2,108,919
GOF	23,113.27	372,662.92	11,752.05	193,213.12	12,257.67	187,749.16
p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Note. This table analyses the price clustering for trades and contracts occurring at digits ending in 0 or 5 (*x.x0 & x.x5*) or at digits different from 0 or 5 (*Rest*) for all the trades (*All trades*), for buyer-initiated trades (*Buyer*), and seller-initiated trades (*Seller*) for the ECX EUA futures contracts with maturities in December 2010, 2011 and 2012. Each panel shows the frequency of the number of transactions *(%Trades*) and the frequency of the total amount of contracts traded *(%Contracts*), both expressed in percentage terms. Each panel also presents the total number of observations (*Total*), the Goodness of Fit Chi-squared statistic (*GOF*), and its p-value. The Goodness of Fit Chi-squared statistic tests the null hypothesis of no difference between the observed distribution and the expected distribution.

Table 5. Example of trading-related variables

Panel A: Trade Volume Information on two days

Day 1		Day 2	
Price	Contracts	Price	Contracts
15.05	10	15.02	10
15.00	1	15.03	2
15.01	1	15.01	3
		15.00	3
		16.00	18
		15.00	3
		15.00	1

Panel B: Trade volume classification for the three variables

Day 1	Sizes	Count	Volume
Full	2	3	12
0 digit	1	1	1
5 digit	1	1	10
0 or 5	2	2	11
Different	1	1	1

Day 2	Sizes	Count	Volume
Full	5	7	40
0 digit	3	4	25
5 digit	-	-	-
0 or 5	3	4	25
Different	3	3	15

Panel C: Trade size percentage by sample

Sizes	Full	0 digit	5 digit	0 or 5	Different
1	3/10	2/5	-	2/6	1/4
2	1/10	-	-	-	1/4
3	3/10	2/5	-	2/6	1/4
10	2/10	-	1	1/6	1/4
18	1/10	1/5	-	1/6	-
Count	10	5	1	6	4

Note. This table shows the classification of the trades according to the variables used in the size analysis. Panel A provides an example of the trade negotiation on two days. Panel B shows how these transactions are distributed according to the distinct trade sizes (*Sizes)*, the frequency of observations (*Count),* and the total volume of contracts traded *(Volume)* for the full sample, for trades where the last decimal is 0, for trades where the last decimal is 5, for trades where the last decimal is 0 or 5, and for trades whose last decimal is different from 0 or 5. Panel C shows the percentage of trade sizes over the two days for each sample.

Table 6. Descriptive statistics of distribution

Panel A: Prices ending in digits 0 or 5 and in digits different from 0 or 5

2010	All trades	Buyer	Seller
Median 0 or 5	9	8	7
Median Rest	10	9	9
K-W: 0&5 vs Rest	0.004	0.001	0.003
2011	All trades	Buyer	Seller
Median 0 or 5	8	6	6
Median Rest	14	10	10
K-W: 0&5 vs Rest	0.001	0.001	0.001
2012	All trades	Buyer	Seller
Median 0 or 5	11	8	8
Median Rest	18	13	13
K-W: 0&5 vs Rest	0.001	0.001	0.001

Panel B: Wilcoxon/Mann–Whitney statistic between Buyer and Seller subsamples

Buyer vs Seller	2010	2011	2012
WMW statistic	0.130	0.036	1.262
p-value	0.897	0.971	0.207

Note. This table presents some statistics and tests related to *Size* distribution, where *Size* refers to the daily number of distinct trade sizes for all the trades (*All trades*), for buyer-initiated trades (*Buyer*), and seller-initiated trades (*Seller*) for the ECX EUA futures contracts with maturities in December 2010, 2011 and 2012. Panel A shows the median of the variable *Size* for prices ending in 0 or 5 and for prices ending in digits different from 0 or 5 (*Rest*), respectively. Panel A also shows the p-value of the Kruskal-Wallis (*K-W*) statistic that tests the null hypothesis of equality in the medians for the different subsamples compared. Panel B shows the Wilcoxon/Mann–Whitney statistic *(WMW statistic)* and its p-value that tests the null hypothesis of equality of the general distribution between *Buyer* and *Seller* subsamples.

Table 7. Determinants of size clustering

	2010		2011		2012	
	Coefficient	p-value.	Coefficient	p-value.	Coefficient	p-value.
α	7.121	0.000	7.029	0.000	7.826	0.000
σ_t	26.237	0.329	-67.896	0.047	29.139	0.429
$Count_t$	0.061	0.000	0.069	0.000	0.066	0.000
Trade $Size_t$	-0.004	0.000	-0.001	0.235	-0.002	0.002
$R3_{H.t}$	-3.453	0.000	-5.003	0.000	-6.459	0.000
$R3_{M.t}$	-0.045	0.943	0.052	0.934	0.080	0.897
$R3_{L.t}$	-3.048	0.000	-3.703	0.000	-4.704	0.000
D_t	1.874	0.000	3.226	0.000	5.003	0.000
D_t x σ_t	37.522	0.197	10.804	0.713	-1.000	0.978
D_t x $Count_t$	-0.032	0.000	-0.035	0.000	-0.034	0.000
D_t x Trade $Size_t$	-0.001	0.328	0.000	0.932	-0.004	0.006
D_t x $R3_{H.t}$	-0.221	0.837	-1.816	0.092	-2.916	0.001
D_t x $R3_{M.t}$	-0.698	0.357	-0.335	0.649	-0.364	0.579
D_t x $R3_{L.t}$	-0.392	0.696	-1.056	0.213	-3.163	0.000
R^2	0.761		0.828		0.786	
Adjusted-R^2	0.759		0.827		0.785	
F-statistic	386.921		709.948		715.657	
Prob (F-statistic)	0.000		0.000		0.000	

Note. This table analyses the possible determinants of size clustering (equation 2). $Size_t$ refers to the daily number of distinct trade sizes. σ_t is the daily volatility. $Count_t$ is the number of trades per day. *Trade* $size_t$ indicates the daily average trade size. $R3_{H,t}$, $R3_{M,t}$, and $R3_{L,t}$ are dummy variables that take value 1 when *R3* is in the intervals [0.95, 1], [-0.025, 0.025], and [-1, -0.95], respectively. *D* is a dummy variable equal to 1 if contract prices end in a price different from 0 or 5, and 0 otherwise.

Chapter III

DO PRICE BARRIERS EXIST IN THE EUROPEAN CARBON MARKET?

1. Introduction

The study of the behaviour of past prices and some other indicators like trading volume is extensively applied in the technical analysis, which is frequently used in the practitioners' world and in a wide number of financial media. Specifically, the financial media tend to use expressions such as key reference points, price barriers, supports or resistances in order to make reference to specific levels of prices that prevent traders from pushing the price of an asset in a certain direction. According to Mitchell (2001 p. 402) a psychological barrier can be viewed as an impediment to an individual's mental outlook, that is, an obstacle created by the mind, barring advance or preventing access. As Murphy (1999 p. 550) points out, in the resistance price or level, the selling interest is sufficiently strong to overcome the buying pressure, while in the support price or level, the buying interest is strong enough to overcome the selling pressure.

Several authors have reported on the existence of price barriers in different markets. De Grauwe and Decupere (1992) and Mitchell and Izan (2006) find that psychological barriers are significant in the dollar/yen market and on various exchange rates involving the Australian dollar. Donaldson and Kim (1993) and Koedijk and Stork (1994) examine the existence of positional effects in stock indexes and find that prices that are multiples of one hundred are approached and transgressed relatively infrequently. Cyree, Domian and Luton (1999) also find evidence of psychological barriers in the conditional moments of the major world stock indices. Regarding commodity markets, Aggarwal and Lucey (2007) document that prices in round numbers act as barriers with important effects on the conditional mean and variance of the gold price series. Finally, Dowling, Cummins and Lucey (2016) study psychological barriers in oil futures markets and show that those levels only appear to influence prices in the pre-credit crisis period of 1990-2006.

These types of studies belong to one of the most researched fields nowadays in finance known as behavioural finance, which proposes psychology and sociology based theories to explain market anomalies. Specifically, the financial literature has suggested several possible explanations for the existence of psychological barriers. The first one relates the barriers with the concept of anchoring, which, according to Slovic and Lichtenstein (1971), is the phenomenon whereby individuals fixate on a recent number that may be held out as being important by informed commentators. In this way, Sonnemans (2006) points out that when an investor buys an asset, he has a target price in mind at which he is willing to sell in the future. The second explanation is related to the clustering effect that makes reference to the fact that investors tend to round off arbitrary rational numbers to integers to simplify their trading process. As Mitchell (2001) indicates, the existence of price clustering does not imply the existence of a barrier. According to Tschoegl (1988), all the psychological barriers take place at round numbers but not all round numbers can be viewed as psychological barriers. Finally, the third explanation of the psychological barriers effect relates the existence of key prices to the possibility of hedging with options contracts, which imply using option exercises prices that are usually round numbers (see Dorfleitner and Klein, (2009 p.269)).

The study about how returns can be affected by the proximity of key levels has attracted the attention of many researchers that have analysed the stock market. Donaldson and Kim (1993) and Ley and Varian (1994) study the impact of key prices on stock index returns and they do not find a way to predict futures returns using these key prices. Another group of papers has analysed the effects of the vicinity of target levels on index volatility. While Dorfleitner and Klein (2009) observe an increase in volatility around barriers, Cyree et al. (1999) and Chen and Tai (2011) only find significant conditional variance effects once the barrier is crossed. Regarding commodities, it is worth mentioning the papers by Aggarwal and Lucey (2007), Lucey and Dowling (2012) and Narayan and Narayan (2014). The first paper shows that the conditional volatility in the gold market changes significantly after crossing barriers in a downward direction. The second paper finds evidence for psychological barriers in both oil and coal price data that affect both the level and the volatility of prices. Finally, the third one finds a negative barrier effect induced by the oil price on firm returns when the oil price reaches US$100 or more per barrel.

In this chapter, we study the presence of price barriers in the European Carbon Market. The reference to specific price levels or range of prices as a resistance or a support is something common among some carbon market analysts that consider that certain values hold special significance for carbon market participants. For instance, during the third quarter of 2012, the price of the European Union Allowances (EUAs) at €8.00 was held by the specialized carbon media as a sign of strength. This was the underlying idea of some quotations that appeared in Reuters Point Carbon such as: “European carbon prices flatlined on Wednesday after trading either side of the psychologically important figure of 8 euros, a resistance level that traders said has been tested for the last four consecutive days.” (Reuters Point Carbon, July 11, 2012); or “EU Allowance prices broke through the psychologically-important 8 euro level to hit a six-week high on Wednesday, but later retreated as speculators took profits, traders said.”

(Reuters Point Carbon, August 22, 2012). Even though these key prices used to be established at round numbers, they also can be found in other levels. Thus a carbon analyst indicated that "Traders had previously spoken of €15.00 as a psychological support level, although many are now pointing to €14.80 as a technical resistance level." (Reuters Point Carbon, October 29, 2010).

This study is in line with several papers that offer empirical evidence as to the efficiency of the European Carbon Market. Daskalakis and Markellos (2008) examined the efficiency of the main exchanges under the European Union Emission Trading Scheme during the first two years of its operation and found that the behavior of the markets under consideration was not consistent with weak-form efficiency. Montagnoli and De Vries (2010) extended the previous paper and their results indicated that, after an inefficient learning period, the carbon market showed signs of restored market efficiency. Similar findings were obtained by Niblock and Harrison (2013). However, Crossland, Li and Roca (2013), for a comparable sample period, documented robust short-term momentum and medium-term overreaction strategies that remained achievable after taking into account transaction costs, and concluded that the carbon market was not informationally efficient. Finally, Palao and Pardo (2012) documented a strong presence of price clustering in carbon markets that was taken as a sign of market inefficiency that could influence trading strategies. Our chapter extends the aforementioned literature by analysing the existence of psychological prices in the European Carbon Market. The presence of resistance or support levels in the EUA prices can offer new insights into market efficiency and the effects these barriers have on returns and volatility when the market is bullish or bearish.

Specifically, we study the existence of key prices in the European Carbon Market and we also analyse how returns, volatility and trading-related variables are affected by their presence. As far as we know, this is the first study that analyses this topic in the European Futures Carbon Market. This market, like energy futures markets, is primarily traded by professional market participants and, consequently, psychological influences on their trading behaviour should play a limited role (see Dowling et al. (2016)). Furthermore, the investigation of psychological prices could offer new insights into the efficiency of the European Carbon Market and the effects these barriers have on returns and volatility when the market is bullish or bearish. The remainder of the paper is organized as follows. Section 2 briefly describes the European Carbon Market and the data used to perform this study. Section 3 provides a definition of barrier and studies its existence. Section 4 investigates the effects of crossing target levels on returns, volatility and trading-related variables such as volume and open interest. Section 5 concludes and proposes some profitable trading strategies based on the detected effects of key prices on carbon returns and volatility.

2. Market description and data

The European Union is the leader in global climate policy and the European Union Emission Trading Scheme (EU ETS) is widely considered as the cornerstone in the fight against climate change. The EU ETS was set up in January 2005 under Directive 2003/87/EC with the aim of limiting total emissions of Greenhouse Gases (GHG) while enabling emissions reductions to be made at the lowest possible cost. The EU ETS is a multinational system that covers the power generators and heavy industry of the 28 member countries of the EU and the three member countries of the European Economic Area (Iceland, Liechtenstein and Norway), which means that the largest emissions market in the world is composed of approximately 12,000 industrial installations and aircraft operators. These installations receive or buy emission allowances which they can trade with one another as needed. However, the installations must monitor and report their emissions for each calendar year and, by 30 April of the following year, each company must surrender enough allowances to cover all its emissions. If they fail to comply, they will have a non-compliance penalty.

The EU ETS is a cap-and-trade system. This system fixes a cap or limit on the total amount of GHGs that can be emitted. This limit is reduced each year and the aim of the EU ETS is to emit 21% less in 2020 than in 2005. This scheme is divided into phases: Phase I, known as the pre-trading period, took place from 2005 to 2007; Phase II ran from 2008 to 2012; Phase III that will cover 2013 to 2020; and Phase IV that will operate from 2021 to 2030.

The main objective in Phase I was to establish a fully functioning emissions market by the start of the Kyoto Protocol commitment. In this Phase, each country presented a National Allocation Plan (NAP) that had to be approved by the European Commission. The EU cap resulted from the aggregation of the NAPs of each member state. The surplus of allowances in Phase I together with the prohibition on transferring any surplus of EUAs to the next year, led the EUA price in this phase to decrease to zero. Phase II took place at the same time as the Kyoto Protocol commitment and, for the first time, the transfer of any surplus of EUAs from one year to the next, known as banking, was allowed. Furthermore, in Phase II, new GHGs were incorporated into the scheme, and the number of member countries increased with the addition of the three member countries of the European Economic Area.

The NAPs system was abandoned in Phase III and replaced with a single EU-wide cap, which will be reduced annually by a constant linear reduction factor. Furthermore, the free assignation of emissions allowances to installations, known as grandfathering, which had characterized both Phases I and II, began to be gradually reduced. In 2013, more than 40% of the allowances were auctioned. The European Commission has also increased its efforts to reduce the surplus of emissions of previous phases through the implementation of two measures: firstly, a short term measure to postpone the auctioning of 900 million allowances until 2019-2020, known as backloading, and, secondly, a long term measure, that proposes the creation of a Market Stability Reserve to address imbalances in supply and demand by adjusting volumes for auctions. The increase in the number of sectors covered in Phase III has contributed to enhancing the importance of the EU ETS as an emissions reduction mechanism.

There are several trading platforms that trade carbon allowances. However, ICE Futures Europe is by far the leading market for European carbon emissions. Specifically, ICE Futures Europe currently offers futures, options and spot contracts on three types of carbon units: EU Allowances (EUAs), EU Aviation Allowances (EUAAs) and Certified Emission Reductions (CERs). However, the majority of the ICE EUA and CER futures and options volume is concentrated in the EUA December Futures Contract for each year, which is widely considered as the carbon price benchmark. The EUA futures contracts are traded in lots, and each lot equals 1,000 CO_2 EU Allowances. Each EUA represents 1 metric tonne of carbon dioxide or equivalent gas. The quotation is in Euro cents per metric tonne and the minimum tick is €0.01 per tonne (i.e. €10 per lot).

ICE Futures Europe market operates an electronic order-driven market with market makers and brokers. The daily session starts with a pre-open period of 15 minutes (from 6:45 a.m. UK local time) to enable market members to input orders in readiness for the beginning of trading. The pre-trading period finishes with a single call auction, where the opening price and the allocated volume are determined by an algorithm. During the continuous session, from 7:00 to 17:00, investors can submit limit orders, market orders, and block orders. The daily settlement price is calculated from the weighted average of the trades taking place from 16:50:00 – 16:59:59 UK local time.

Specifically, the sample period analysed in this paper goes from 18 December 2007 to 17 December 2012 and thus spans 1,272 trading days. The series contain the time stamp, the price, and the size of the transaction for all the trades that took place for the front contract of Phase II from 2008 to 2012. Furthermore, we also have the data for the open interest at the end of each day. Carchano, Medina and Pardo (2014) assess the rollover criteria both for EUAs and CERs. Following them, we have rolled on the last trading day in order to construct a continuous series. Table 1 includes the main statistics for price and trading volumes for the continuous series. The sample contains 1,306,765 transactions for a total trading volume of 9,201,096 futures contracts and the price oscillates between €5.61 and €29.69. The most repeated price is €15.25. The majority of the transactions have a size of 1 lot and the maximum number of futures contracts traded in one transaction was 1,682.

Figure 1 shows the evolution of the intraday data series of the price of the EUA December futures front contract during Phase II. At a glance it reveals an overall downward trend that can be explained by two factors: the over-allocation of EUAs inherited from Phase I and the global economic downturn that resulted in less carbon emissions. The European temperatures during the winter 2008-2009 were below the average, a fact that would be expected to increase demand for electricity and thus the price of EUAs. However, after reaching a maximum price of €29.69 in July 2008, the price slumped until bottoming out at €8.49 in February 2009, which can be explained by the serious economic recession that more than offset the low temperatures. . Following Creti, Jouvet and Mignon (2012), carbon prices in Phase II were affected by other events over 2009 and 2010, such as the wait-and-see attitude of the international negotiations in the Copenhagen summit (December 2009), the failure by allowance sellers to pay back to Member States the VAT they collect (December 2008 to May 2009), and several phishing attacks that hacked into registry accounts (end of 2010). In June 2011, the draft of the European Commission about the Energy Efficiency Directive raised concerns about the (lower) demand for allowances in Phase III, triggering an additional decline in prices. From December 2011 to December 2012 the price oscillated between €6 and €10. [13]

Looking at Figure 1, it could be inferred that more than one unexpected event could have affected the carbon price. However, Creti et al. (2012) have shown that, after considering all the events mentioned in the previous paragraph, an equilibrium relationship existed between the EUA carbon price and its market fundamentals during Phase II.

[13] See Ellerman and Buchner (2008) and Rickels, Görlich and Oberst (2012) for a further description of the dynamics of EUA prices during Phase I and II.

3. The barrier level and the barrier band

Resistance and support levels are identified by traders when systematically a quotation of an asset cannot exceed a certain price in a bullish market or drop below a certain price in a bearish market, respectively. In order to detect them, we follow Dorfleitner and Klein (2009) who define the M-values as 100 classes of digits (t = 00–99) on which the price can land or be passed based on a two-digit representation. In our study, we have analysed the level 0, defined as the two numbers that represent the decimal part of the price, and the level 1, identified as the pair of the unit and the first decimal. In particular, we define the M values as:

$$M_t = z - Integer(z/100) \times 100 \; with \; z = Integer(P_t/10^{l-2})$$

where P_t is the EUA futures price at time *t* and *l* is the barrier level (0 or 1). For instance, if P_t = € 5.68, the M-values would be 68 and 56 for the level 0 and 1, respectively. These M-values allow us to calculate the relative frequencies of different prices at different barrier levels.[14]

Figure 2 presents the empirical distribution of M-values at both levels. Figure 2a depicts the distribution of the M-values for the level 0. The peaks of M-values multiples of 5 are in accordance with the previous empirical evidence found by Palao and Pardo (2012, 2014). They document that the European Carbon Futures Market is characterized by a strong presence of price and size clustering at prices ending in digits 0 and 5. Figure 2b plots the empirical distribution of the M-values at level 1. At first glance it shows that EUA tends to be traded around

[14] We have analyzed only the levels 0 and 1. An analysis of higher levels does not make sense due to the lack of EUA prices higher than €30.

M-values of 50 and 70 (prices from €5 to €7). As in the level 0, the empirical distribution presents severe deviations from a uniform distribution.

If a barrier level does exist, then the empirical distribution of the M-values should be biased and the observed frequency distribution of EUA transaction prices would differ from the theoretical distribution. Although this fact can be easily observed from Figure 2, we have tested formally whether M-values distributions are biased. To this aim, we have performed a chi-squared goodness of fit test for both full samples of M-values.

Given that EUA transaction prices in the sample range between €5.61 and €29.69 (2,409 possible different prices), the theoretical distribution of M-values at both levels should not follow a uniform distribution. For this reason, unlike other articles that suppose that each M-value is expected to occur the same number of times, we have calculated the expected (theoretical) frequency as 1,306,765 observations times the fraction of each M-value in the population.

The results obtained are 182,451.984 for level 0 and 417,660.656 for level 1, respectively. The χ^2-statistic with 99 degree of freedom and with a probability of 0.1% takes a value of 148.23. Therefore, the empirical distributions of the M-values at both levels differ from their theoretical distributions.[15]

Dorfleitner and Klein (2009, p.272) consider that "the barrier cannot be viewed as a specific number and define the barrier as an interval with a certain length around the barrier level". Following this idea, we distinguish between the barrier

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[15] The application of these tests can face different challenges when the size of the sample is small, as the Benford's Law shows. This phenomenon points out that the first digits of a series increase following a logarithmic model and, as De Ceuster, Dhaene and Schatteman (1998) suggest, this issue is crucial for small samples. We consider that, given the large size of our sample (1,306,765 transactions), this effect will not generate a relevant distortion in our analysis.

level, given by each M-value, and the barrier band, which is an interval of M-values around the barrier level. Therefore, we have analysed the level 0 and the level 1 taking into account intervals of +/-1 and +/-3 M-values around the barrier level, as the possible barrier bands. Furthermore, we have also taken into account a zero range that, in fact, implies taking the level as a strict barrier.[16] See Figure 3 for a graphical example of how the barrier bands have been defined:

Taking into account this broader definition of barrier, what is relevant is not only the occurrence in the strict prices but also what happens around the proximity of a possible psychological price. To study both issues, we perform the barrier proximity test proposed by Donaldson and Kim (1993):

$$f(M_t) = \alpha + \beta D_t + \epsilon_t$$

where $f(M_t)$ is the frequency of the 100 M-values minus 1% and D_t is a dummy variable that takes the value 1 when the M-value *t* belongs to a barrier band. If the M-values followed a uniform distribution, the theoretical value for each M-value, from 00 to 99, would be 1% and the parameter β will be equal to 0. Negative values of β show less density around barriers and positive values just the opposite.[17]

At this point, it is important to highlight the controversy that exists in the literature on price barriers regarding the interpretation of the sign of β around the price level. Authors like Donaldson and Kim (1993), Aggarwal and Lucey (2007) and

[16] The choice of both the barrier and the intervals depends on the range of the prices of the asset to be analyzed. For example, Donaldson and Kim (1993) study price barriers in the Dow Jones Industrial Average and define barriers at 100-levels of the index and intervals of 2%, 5% and 10% around the level; Dorftleitner and Klein (2009) examine four European stock indexes and eight major German stocks and define the barriers as the multiples of 1000, 100, 10 and 1 and intervals of 2%, 5%, 10% and 25%; finally, Aggarwal and Lucey (2007) examine psychological barriers in gold prices at 10s and 1s digits fixing ranges of 2% and 5%.

[17] The regressions through the study have been carried out using both ordinary least squares and the Newey and West correction that accounts for heteroskedasticity and serial correlation problems.

Jang, Kim, Kim, Lee and Shin (2015) suggest that if a barrier exists, we should expect to find less density around the price barriers. The rationale is that the market finds it difficult to reach these levels during upturns or downturns caused by the considerable influx of selling or buying orders at those prices, that is, both buyers and sellers become less aggressive fearing a turn in the market trend. Therefore, the null hypothesis of no barriers implies that β should be zero, while the alternative hypothesis implies that β should be negative. However, other authors like Dorfleitner and Klein (2009) and Chen and Tai (2011) argue that the observation frequencies of M-values next to barriers could be even higher, because it takes some "effort" for the prices to cross this barrier. As a consequence, they assume that if β is zero, there is no price barrier effect; however, the alternative hypothesis is that β may have significant negative or positive values.

Table 2 presents the results of the estimation of the barrier proximity test for levels 0 and 1. In both cases, the Panels show the results for the five M-values with the highest observed frequencies.[18] Panel A of Table 2 presents the results for the barrier proximity test for 0-level. The β coefficients are always positive and significant at the 1% level in the strict barriers, which indicates that EUA trades take place more than expected at those prices. For example, EUA prices are traded 0.9930% more than expected at the M-value 00. This also occurs for the rest of the M-values that have been chosen (50, 70, 80 and 90). Furthermore, the $\beta's$ become non-significantly different from zero further away from the barrier

[18] The rationale for choosing the most common M-values both for levels 0 and 1 is that if barriers exist, they should take place on or around the most frequent trading prices, which are the most difficult to overcome or at the levels where most limit orders are posted. However, we have estimated the results for the complete set of M-values and they are available from the authors upon request.

level. Therefore, although we detect price barriers at the 0-level, we do not observe the existence of barrier bands at such level.

Panel B of Table 2 presents the results for level 1. In this case, we have chosen to analyse the five multiples of the five most repeated M-values. The β coefficients are again positive and significant at the 1% level in the strict barriers. However, unlike what happens at level 0, if we choose wider ranges, the coefficients are in general positive and significant at the 1% level. For example, EUA prices are traded 0.8949% more than expected at the M-value 70 (= €7) but they are also traded with a frequency more than expected at intervals of +/-1 and +/-3 M-values around the barrier level of €7.

These findings indicate that price barriers are observed in EUA prices with a second decimal ending in 0 and for round EUA prices such as €7, €8, €13, €14.5, and €15, among others. In these last prices, the existence of a barrier band in the proximity of the target level has also been detected.

As we have mentioned, one of the possible explanations for the existence of psychological barriers relates the key prices to the option exercise prices, which are usually round numbers. For this reason, we have calculated the percentage of the number of options traded for each strike price with delivery in December 2012. Despite the fact that minimum strike price increments can be €0.01, all the options are traded with rounded exercise prices. In Figure 4, we observe peaks in exercise prices such as €12, €14, €15, €18, €20 and €27. Note that this range of prices overlaps with the potential barriers obtained from the analysis in Table

2, and consequently, option exercise prices could help to explain why EUA psychological barriers exist.[19]

4. Effects of target levels

4.1. Returns and volatility tests

In this section we study if EUA returns and volatility are affected by the proximity of key levels. Firstly, we analyse if there is statistically different behaviour in terms of returns and volatility on those days when a potential barrier has been touched at any time during the trading session. We compute the returns as the natural logarithm of the quotient among the settlement prices of the EUA front contract:

$$r_t = \log(\mathrm{P_t}) - \log(P_{t-1})$$

and the intraday volatility has been calculated following the measure proposed by Parkinson (1980):

$$\sigma_t = \sqrt{\frac{1}{4log2}(logH_t - logL_t)^2}$$

where H_t is the highest and L_t are the lowest traded prices on day *t*.

Specifically, we perform the Wilcoxon's rank test to compare the median of the returns and volatility on those days on which a barrier or barrier band has been crossed with the medians of those days on which a barrier has not been crossed. In our case, we assume as the alternative hypothesis that the return and intraday volatility of these days on which a barrier has been reached is greater than on those days on which it has not. Table 3 shows the Wilcoxon's rank test between

[19] All the information about the characteristics of the EUA futures options contract are listed in https://www.theice.com/products/196/EUA-Futures-Options. (last accessed on April 27, 2015).

the medians of the returns. Both Panels A and B offer similar results. We cannot reject the null hypothesis of equality in medians in both panels. Therefore, there is no evidence of an effect of crossing barriers or barrier bands on returns either at level 0 or at level 1.

Table 4 shows the results for the one-sided Wilcoxon's rank test. Now, we are comparing the median of the intraday volatility on days where a barrier or a barrier band have been touched with those which not. We reject the null in favour of a higher intraday volatility on days on which barriers or barrier bands have been touched in 24/30 (= 80%) of the cases. The results of the two-sided Wilcoxon's rank test for intraday volatilities, not reported in the paper, show the rejection of the null hypothesis of equality of the medians in 29/30 (= 96.66%) of the cases. Therefore, daily returns are not affected when transaction prices are in the vicinity of key prices but intraday volatility is abnormally high or low on these days.

4.2. Effects on returns and volatility conditioned to market trends.

Cyree et al. (1999) show that the behaviour of returns and volatility could be different in the proximity of target levels depending on the market trends before and after the barrier level or the barrier band has been touched. Therefore, following them, we adapt a dummy analysis to assess the influence of EUA barriers in four different scenarios. Specifically, we split the market trend in a bullish or a bearish market, and we analyse the impact on returns and volatility before and after the barrier is touched. Following the suggestions from the carbon traders, we consider that the carbon market has an upward (downward) movement if the accumulated return of the 3 days prior to the day the barrier is touched is positive (negative).

The rationale is to separate indicator variables for the pre-crossing and post-crossing sub-periods, and upward or downward moves. Specifically, UB (Upward Before) is a dummy that takes value 1 for the three days prior to an upward movement through a barrier and 0 otherwise; UA (Upward After) is a dummy that takes value 1 for the three following days after the price crosses a barrier in an upward movement, and 0 otherwise; DB (Downward Before) is a dummy that takes value 1 for the three previous days before a downward movement through a barrier and 0 otherwise; and DA (Downward After) is a dummy that takes value 1 for the three days following the price passing a barrier in a downward movement, and 0 otherwise.

Firstly, the analysis is focused only on those days on which a key level has been touched. Then, we compare the 3-day return for the sub-periods before and after, in order to check the behaviour of the conditional mean when EUA prices are in the proximity of potential barriers. For example, if we observe negative or zero returns after a significant upward movement, the key level could be considered as a resistance level.

Secondly, we have also analysed the impact on the daily volatility. According to the methodology employed by Cyree et al. (1999), we have run a joint analysis of returns and volatilities at the same time.[20] For this purpose, we will estimate an ARMA-GARCH model. We have chosen to employ an EGARCH (1,1). This parameterization has also been used by another authors, like Medina and Pardo

[20] As Cyree et al. [1999] points out, the distributional shifts implied by psychological barriers invalidate the basic assumption of OLS.

(2013) and Chen, Wang and Wu (2013), who chose this model as the most appropriate in the EUA case.

More precisely, the EGARCH(1,1) model employed to estimate the effect of key levels on return and volatility is composed of two equations. The first one is the return estimation, where the EUA return, calculated as in the previous section, is regressed on the four dummy variables UB, DB, UA, DA described above, and the error term follows a normal distribution with zero mean and variance V_t:

$$R_t = \alpha + \beta_{UB}UB_t + \beta_{DB}DB_t + \beta_{UA}UA_t + \beta_{DA}DA_t + \epsilon_t$$

The variance, V_t, follows a process described below that also includes the four dummy variables in order to analyse if psychological barriers affect EUA volatility:

$$\begin{aligned} lnV_t^2 = \delta + \theta\left(|\epsilon_{t-1}| - \sqrt{2/\pi}\right) + \phi_1\epsilon_{t-1} + \phi_2 lnV_{t-1}^2 + \phi_{UB}UB_t \\ + \phi_{DB}DB_t + \phi_{UA}UA_t + \phi_{DA}DA_t + \omega_t \end{aligned}$$

where $\theta\left(|\epsilon_{t-1}| - \sqrt{2/\pi}\right) + \phi_1\epsilon_{t-1}$ is the conditional variance.

Table 5 shows the effects of psychological barriers when we estimate returns and volatility together. As we can see in Panel A of Table 5 for the level 0, all the 3-day returns for the sub-period before the touch of the barrier are significantly different from zero, being positive the upward movements (UB) and negative the downward ones (DB). The 3-day returns for the sub-period after are not significantly different from zero in 27 out of 30 cases analysed. Only three (Upward After) scenarios are significantly negative at the 1% level. Therefore, the prices after touching a barrier remain around it or rebound in the opposite direction. Regarding volatility, the results presented in Panel A show that volatility is greater before touching the barrier and lower after touching it for all the cases at the 1% of significance level.[21] The strong evidence of changes in the conditional variances of returns observed in the vicinity of EUA price barriers, especially in downward movements, is in line with the findings obtained by Aggarwal and Lucey (2007) for the gold market and can be explained by the greater uncertainty about the evolution of the quotation before the prices touch a barrier.

Panel B of Table 5 presents the results for the joint estimation of returns and daily volatility for the level 1. We observe, as in the previous case, that all the 3-day returns for the sub-periods before the touch of the barrier are significantly different from zero at the 1% level. However, after touching the barrier the findings are not conclusive. In some bullish scenarios the prices continue increasing after breaking the barrier (X3.0X) while in others the prices remain around the barrier (X8.0X) or go in the opposite direction (X4.5X). This miscellany of results is also observed for the conditional volatility.

4.3. Effects on trading-related variables conditioned to market trends.

The last contribution regarding the study of the effects of barriers is based on an analysis of how daily volume and open interest are affected by the proximity of key levels. The daily trading volume accounts for the amount of trading activity that has taken place in a specific contract on a trading date. On the contrary, the daily open interest indicates the number of outstanding contracts at the end of a trading day. Following Lucia and Pardo (2010), there is a convention in financial literature that the daily trading volume primarily proxies movements in speculative

[21] Following Aggarwal and Lucey (2007) and Cyree et al. (1999), we have applied a chi-squared test to the coefficients of the variance equation in order to test if there is no difference in the conditional variances before and after an upward or downward touching. We reject the null in both cases confirming a decrease in the levels of conditional volatility in both scenarios in all the prices. For the sake of space, these results are not presented in the paper but are available upon request.

activity, whereas the daily open interest variable captures hedging activities in derivatives markets, since open interest excludes by definition intraday traders.

To look into the effects of price barriers on speculative and hedging activities, we have regressed the four dummy variables UB, DB, AB and AD against the logarithm of the volume, obtaining the following expression:

$$\log(Volume_t) = \alpha + \beta_{UB}UB_t + \beta_{DB}DB_t + \beta_{UA}UA_t + \beta_{DA}DA_t + \epsilon_t$$

where $Volume_t$ is the total trading volume at day *t*.

Results are shown in Table 6. Panel A shows the effects of key prices in volume for level 0. We observe that when the market is in an upward movement, the volume decreases in all the cases. In a bearish scenario, only prices XX.50 and XX.70 show a decrease in the volume before reaching the barrier. Panel B presents the results for the effects of psychological prices in volume for level 1. In this case, we do not find any common pattern in any scenario. The effect of observing low trading volumes when the price is near a barrier in a bullish market could be explained by the argument that speculators do not believe that the trend will last much longer. As a consequence, they decide to wait and postpone their trading activity.[22]

Finally, we have performed a similar analysis taking into account the daily open interest. We have not observed any significant change in the levels of the open interest before or after crossing the key prices, neither in upward nor in downward

[22] In order to test if the global financial crisis affected return and/or volume dynamics, we have repeated the estimations of equations (5), (6) and (7) only for the period that goes from 3 March 2008 to 31 March 2009. Given that the results are qualitatively similar to those presented in the paper for the whole sample, we have decided not to include them but they are available upon request.

movements. Therefore, we hypothesize that hedgers are not affected by the presence of barriers in EUA prices.[23]

5. Conclusions

This study investigates the existence of psychological prices in the ICE ECX futures market taking into account intraday transaction data. Preliminary tests show the presence of key levels and barrier bands in EUA futures prices with a second decimal ending in 0 and for round EUA prices such as 7, 8, 13, 14.5, and 15, among others. Both price clustering and rounded exercise prices in EUA options give support to the existence of these key prices.

We have observed that once the price has touched a key level, EUA prices remain around it or rebound in the opposite direction. Our analysis also shows that intraday volatility is greater before a barrier has been reached and decreases after touching it. Regarding trading volume, we observe that it decreases in upward movements around barriers. Therefore, EUA return and volume dynamics are affected by the existence of price barriers at round prices ending in zero.

In summary, the proximity to a barrier contains information about the magnitude of the deviation of return and volatility from their expected values. Both results are difficult to reconcile with the weak-form of the efficient market theory. The use of this information can help carbon traders to make better decisions in the way they manage their trading activity. For example, if we are in a bullish scenario and traders know that EUA returns increase when the quotations are near the

[23] These results are not included for the sake of brevity, but they are available upon request.

barrier, they could increase their trading activity by buying EUAs before the barrier is reached and selling them once the barrier has been touched. Furthermore, if an EUA option trader knows that the volatility is higher before the EUA price reaches the key level and lower after it, she could develop a strategy based on selling EUA options before the price touches the key level and buying them after it.

All in all, we have shown that in a market as complex as the carbon market, in which the predominant role is that of professional traders, there exist certain price levels that modify the behaviour of the market participants. Our results are in line with those obtained by Menkhoff (2010) who shows that equity and bonds fund managers, who are viewed as highly qualified market participants, tend to use technical analysis, especially in the short term.

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Annex: tables and figures

Table 1. Descriptive statistics

	Price	Volume
Mean	13.02	7.04
Std. Deviation	4.75	15.48
Min	5.61	1.00
Max	29.69	1,682.00
Mode	15.25	1.00
Q_1	6.01	1.00
Median	6.15	3.00
Q_3	6.24	3.00
Skewness	0.79	15.90
Kurtosis	3.69	629.02

Note: The table shows some descriptive statistics for the series of prices and trading volume for the period 18 December 2007 to 17 December 2012. The statistics reported for both distributions are the mean, the standard deviation, the minimum, the maximum, the most repeated price/size, the median of the distribution, the first quartile (Q_1), the third quartile (Q_3), and the coefficients that measure the skewness and the kurtosis of the distributions.

Table 2. Barrier Proximity Test

Panel A. Level 0

		XX.00	XX.50	XX.70	XX.80	XX.90
	Strict	-0.0099	-0.0087	-0.0083	-0.0088	-0.0095
α	+/-1	-0.0059	-0.0030	-0.0056	-0.0050	-0.0057
	+/-3	0.0023	0.0081	-0.0012	0.0011	-0.0005
	Strict	0.9930***	0.8729***	0.8291***	0.8842***	0.9454***
β	+/-1	0.1982	0.0996	0.1855*	0.1670	0.1916
	+/-3	-0.0330	-0.1157	0.0172	-0.0157	0.0076
	Strict	7.0572	5.4531	4.9201	5.5960	6.3966
R^2	+/-1	0.8267	0.2088	0.7237	0.5870	0.7725
	+/-3	0.0511	0.6305	0.0139	0.0115	0.0027

Panel B. Level 1

		X3.0X	X4.5X	X5.0X	X7.0X	X8.0X
	Strict	-0.0085	-0.0084	-0.0078	-0.0110	-0.0059
α	+/-1	-0.0206	-0.0215	-0.0216	-0.0293	-0.0203
	+/-3	-0.0414	-0.0466	-0.0526	-0.0652	-0.0349
	Strict	0.6444***	0.6353***	0.5734***	0.8949***	0.3819***
β	+/-1	0.6175***	0.6482***	0.6523***	0.9084***	0.6061***
	+/-3	0.5621***	0.6368***	0.7224***	0.9018***	0.4695***
	Strict	1.4466	1.4059	1.1455	2.7900	0.5081
R^2	+/-1	3.9042	4.3030	4.3565	8.4504	3.7612
	+/-3	7.2392	9.2911	11.9538	18.6320	5.0508

Note: Panel A (B) shows the results expressed in percentages for the Barrier Proximity Test for Level 0 (1) at strict prices and for two different barrier bands. ***, ** and * indicate significance at 1%, 5% and 10%, respectively. R^2 adjusted is expressed in percentage.

Table 3. Wilcoxon's rank test between medians of returns

Panel A. Level 0

		XX.00	XX.50	XX.70	XX.80	XX.90
	M_b/M_{nb}	-0.0022/0.0004	-0.0013/0.0000	0.0004/0.0000	-0.0019/0.0007	-0.0020/0.0007
Strict	# Obs	603	584	589	600	627
	Value	1.2428	0.4479	0.8535	1.3051	1.3666
	M_b/M_{nb}	-0.0019/0.0000	-0.0009/0.0000	-0.0004/0.0000	-0.0013/0.0846	-0.0020/0.0007
+/-1	# Obs	634	603	615	633	652
	Value	1.2745	0.1806	0.6448	1.0341	1.4167
	M_b/M_{nb}	-0.0013/0.0000	-0.0007/0.000	0.0012/0.0000	-0.0014/0.0007	-0.0013/0.0000
+/-3	# Obs	666	653	661	686	702
	Value	0.9802	0.0349	1.0674	1.4188	0.9444

Panel B. Level 1

		X3.0X	X4.5X	X5.0X	X7.0X	X8.0X
	M_b/M_{nb}	0.0004/0.0000	0.0000/0.0000	-0.0002/0.0000	-0.0022/0.0000	-0.0018/0.0000
Strict	# Obs	124	140	120	104	85
	Value	0.2764	0.0095	0.3049	0.5130	0.5963
	M_b/M_{nb}	0.0012/0.0000	0.0000/0.0000	0.0000/0.0000	0.0000/0.0000	-0.0013/0.0000
+/-1	# Obs	160	195	168	147	114
	Value	0.9290	0.1601	0.4411	0.0634	0.5108
	M_b/M_{nb}	0.0015/-0.0006	0.0000/0.0000	0.0007/-0.0010	0.0014/0.0000	-0.0013/0.0000
+/-3	# Obs	222	273	261	210	154
	Value	0.9236	0.1828	0.5301	0.3610	0.7994

Note: The table shows the Wilcoxon's rank test between the median of returns on days where a barrier or barrier band has been touched and those where it has not. The null hypothesis tests the equality in medians against the alternative hypothesis that tests if the median on days on which a barrier has been reached is greater than the median on those days on which it has not. Panel A (B) shows the results for the psychological barriers considered in level 0 (1). The test has been performed for the strict barrier and +/-1 and +/-3 M-values above and below the strict barrier. M_b/M_{nb} indicates the median of returns of days when a barrier has been touched and the median of returns of days when a barrier has not been touched, respectively. *# Obs* is the number of days on which a barrier or barrier band has been reached and *Value* is the Wilcoxon's rank test statistic. ***, ** and * indicate significance at 1%, 5% and 10%, respectively.

Table 4. Wilcoxon's rank test between medians of intraday volatility

Panel A. Level 0

		XX.00	XX.50	XX.70	XX.80	XX.90
Strict	M_b/M_{nb}	0.0168,0.0109	0.0146,0.0111	0.0166,0.0112	0.0170,0.0110	0.0167,0.0107
	Value	13.5076***	9.1853***	11.4879***	12.5605***	13.2362***
+/-1	M_b/M_{nb}	0.0166,0.0108	0.0163,0.0111	0.0165,0.0111	0.0167,0.0110	0.0167,0.0106
	Value	13.5202***	11.1988***	11.4845***	12.3878***	13.8184***
+/-3	M_b/M_{nb}	0.1165,0.0464	0.1165,0.0450	0.0163,0.0109	0.0163,0.0107	0.0165,0.0105
	Value	13.742***	10.3826***	11.7115***	12.4374***	13.7035***

Panel B. Level 1

		X3.0X	X4.5X	X5.0X	X7.0X	X8.0X
Strict	M_b/M_{nb}	0.0151,0.0131	0.0115,0.0135	0.0113,0.0134	0.0179,0.0129	0.0217,0.0128
	Value	2.2838**	2.5448	2.9226	3.9048***	7.2407***
+/-1	M_b/M_{nb}	0.0138,0.0132	0.0110,0.0137	0.0106,0.0136	0.0165,0.0129	0.0187,0.0127
	Value	1.4599*	4.6123	4.721	3.8744***	7.5086***
+/-3	M_b/M_{nb}	0.0140,0.0131	0.0108,0.0138	0.0101,0.0139	0.0161,0.0128	0.0180,0.0125
	Value	2.246**	6.5761	7.2413	3.7664***	8.0100***

Note: The table shows the Wilcoxon's rank test statistic between the median of the intraday volatility on days where a barrier or barrier band have been touched and those where it has not. The null hypothesis tests the equality in the intraday volatility against the alternative hypothesis that tests if the median on days on which a barrier has been reached is greater than the median on those days on which it has not. Panel A (B) shows the results for the psychological barriers considered in level 0 (1). The test has been performed for the strict barrier and +/-1 and +/-3 M-values above and below the strict barrier. M_b/M_{nb} indicates the median of intraday volatility of days when a barrier has been touched and the median of intraday volatility of days when a barrier has not been touched, respectively, and *Value* is the Wilcoxon's rank test statistic. ***, ** and * indicate significance at 1%, 5% and 10%, respectively.

Table 5. Returns and variance behaviour on days with psychological prices

Panel A. Level 0

		XX.00	XX.50	XX.70	XX.80	XX.90
β_{UB}	Strict	0.0106***	0.0132***	0.0117***	0.0104***	0.0120***
	+/-1	0.0102***	0.0128***	0.0117***	0.0114***	0.0125***
	+/-3	0.0112***	0.0122***	0.0117***	0.0118***	0.0123***
β_{DB}	Strict	-0.0121***	-0.0110***	-0.0122***	-0.0129***	-0.0128***
	+/-1	-0.0123***	-0.0112***	-0.0121***	-0.0130***	-0.0127***
	+/-3	-0.0115***	-0.0116***	-0.0118***	-0.0130***	-0.0122***
β_{UA}	Strict	-0.0002	-0.0016	-0.0017	-0.0019*	-0.0002
	+/-1	-0.0004	-0.0015	-0.0015	-0.0021*	-0.0006
	+/-3	0.0000	-0.0023**	-0.0017	-0.0016	0.0001
β_{DA}	Strict	-0.0010	-0.0011	0.0001	-0.0002	-0.0008
	+/-1	-0.0009	-0.0003	0.0002	-0.0001	-0.0011
	+/-3	-0.0012	-0.0013	0.0004	-0.0002	-0.0011
ϕ_{UB}	Strict	0.1546***	0.0642***	0.0827***	0.1124***	0.1370***
	+/-1	0.1376***	0.0810***	0.0723***	0.0946***	0.1323***
	+/-3	0.1362***	0.0841***	0.0724***	0.0889***	0.1279***
ϕ_{DB}	Strict	0.2898***	0.2405***	0.2112***	0.2677***	0.2642***
	+/-1	0.2718***	0.2557***	0.1955***	0.2498***	0.2568***
	+/-3	0.2826***	0.2471***	0.1995***	0.2348***	0.2621***
ϕ_{UA}	Strict	-0.1760***	-0.1040***	-0.1087***	-0.1248***	-0.1585***
	+/-1	-0.1559***	-0.1227***	-0.0918***	-0.1137***	-0.1550***
	+/-3	-0.1556***	-0.1268***	-0.0906***	-0.1090***	-0.1527***
ϕ_{DA}	Strict	-0.2440***	-0.2003***	-0.1537***	-0.2237***	-0.2204***
	+/-1	-0.2098***	-0.2118***	-0.1276***	-0.2035***	-0.2124***
	+/-3	-0.2408***	-0.1984***	-0.1202***	-0.1927***	-0.2265***
R^2 adjusted	Strict	17.7286	18.2035	19.2460	18.5994	19.7592
	+/-1	17.6368	18.1999	19.5418	19.4636	20.2197
	+/-3	18.3416	19.0902	19.7489	20.3937	21.0073

Panel B. Level 1

		X3.0X	X4.5X	X5.0X	X7.0X	X8.0X
β_{UB}	Strict	0.0116***	0.0111***	0.0093***	0.0096***	0.0153***
	+/-1	0.0106***	0.0120***	0.0106***	0.0116***	0.0156***
	+/-3	0.0125***	0.0129***	0.0126***	0.0129***	0.0167***
β_{DB}	Strict	-0.0127***	-0.0062***	-0.0048******	-0.0089***	-0.0185***
	+/-1	-0.0154***	-0.0084***	-0.006***	-0.0114***	-0.0186***
	+/-3	-0.0159***	-0.0097***	-0.0079***	-0.0110***	-0.0134***
β_{AB}	Strict	-0.0003	-0.0042**	-0.0032**	-0.0005	-0.0023
	+/-1	0.0036**	-0.0026*	-0.0016	0.0001	-0.0024
	+/-3	0.0040**	-0.0022	-0.0018	-0.0007	-0.0043
β_{DB}	Strict	0.0000	-0.0021	-0.0025	-0.0004	0.0018
	+/-1	0.0019	-0.0012	-0.003**	0.0001	0.0037
	+/-3	0.0008	-0.0019	-0.0036*	0.0001	-0.0040
ϕ_{UB}	Strict	-0.1847***	-0.1738***	-0.1388***	-0.0240	0.0782
	+/-1	-0.2057***	-0.1599***	-0.1579***	-0.0835*	0.0401
	+/-3	-0.2160***	-0.1733***	-0.2146***	-0.0369	0.0436
ϕ_{DB}	Strict	0.0938**	0.0926*	0.0713	0.1958***	-0.1392*
	+/-1	0.0514	0.0200	-0.0245	0.1119**	-0.1158
	+/-3	0.0465	0.0481	0.0385	0.0354	0.0338
ϕ_{UA}	Strict	0.0810	0.1228***	0.0210	-0.0917*	-0.0457
	+/-1	0.0762	0.1069***	0.0183	-0.0371	0.0160
	+/-3	0.1289**	0.1061***	0.0879**	0.0204	-0.0666
ϕ_{DA}	Strict	-0.0286	-0.1209**	-0.0603	-0.0709	0.2777***
	+/-1	0.0310	-0.0391	0.0512	-0.0053	0.2078***
	+/-3	0.0033	-0.0582	-0.0015	-0.0210	0.1276**
R^2 adjusted	Strict	2.7595	2.5408	1.6195	2.9609	4.1711
	+/-1	3.5425	3.1922	2.5991	3.8686	4.7150
	+/-3	5.2138	3.7977	3.9544	5.1054	5.5462

Note: The table shows the impact on returns and variance before and after a psychological price when prices are in a bullish or bearish market. UB is a dummy variable which takes value 1 during the 3 days before a psychological price is touched if the market is bullish and 0 otherwise, DB will take value 1 during the 3 days before reaching the psychological price if the market is bearish and 0 otherwise, UA will take value 1 during the 3 days after reaching a psychological price if the market before the price touches the barrier has been bullish and 0 otherwise, and DA will be equal to 1 during the 3 days if the market before the price touches the barrier has been bearish. In Panel A are shown the results for Level 0 and in Panel B we can find the results for Level 1. ***, ** and * indicate significance at 1%, 5% and 10%, respectively. R^2 adjusted is expressed in percentage.

Table 6. Volume behaviour on days with psychological prices

Panel A. Level 0

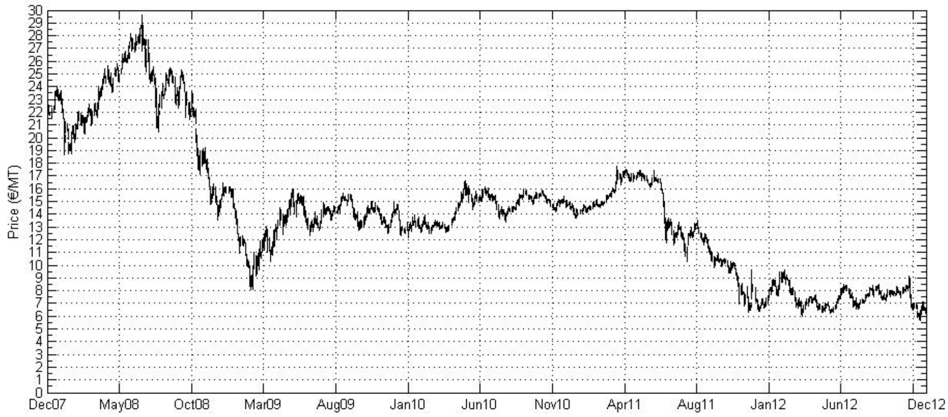
		XX.00	XX.50	XX.70	XX.80	XX.90
β_{UB}	Strict	-0.1423**	-0.2570***	-0.2168***	-0.1505**	-0.1356**
	+/-1	-0.1365**	-0.2571***	-0.2164***	-0.1779***	-0.1204*
	+/-3	-0.1210*	-0.2711***	-0.2173*	-0.1421**	-0.1175*
β_{DB}	Strict	-0.1024	-0.1954***	-0.1657***	-0.0663	-0.0780
	+/-1	-0.0903	-0.2325***	-0.1947***	-0.0585	-0.0731
	+/-3	-0.0898	-0.2307***	-0.1920***	-0.0681	-0.0887
β_{UA}	Strict	-0.1370*	-0.2277***	-0.2263***	-0.1651**	-0.1564**
	+/-1	-0.1421*	-0.2071***	-0.2241***	-0.1817**	-0.1429**
	+/-3	-0.1361*	-0.2091***	-0.2158***	-0.1444**	-0.1254*
β_{DA}	Strict	-0.0065	-0.0657	-0.0226	0.0155	-0.0002
	+/-1	0.0085	-0.0701	-0.0283	0.0326	0.0076
	+/-3	0.0061	-0.0792	-0.0404	0.0431	0.0248
R^2 adjusted	Strict	1.7459	6.5807	4.5411	2.0045	1.7819
	+/-1	1.6863	6.7542	4.9037	2.7935	1.3955
	+/-3	1.4451	6.6482	4.8524	1.8057	1.2436

Panel B. Level 1

		X3.0X	X4.5X	X5.0X	X7.0X	X8.0X
β_{UB}	Strict	-0.1021	-0.238**	-0.2141*	0.1388	0.2665*
	+/-1	-0.1045	-0.1365	-0.2284**	0.1606	0.2107
	+/-3	-0.1470	-0.1796*	-0.1928*	0.0628	0.2400*
β_{DB}	Strict	-0.1009	-0.2398**	-0.0261	0.1589	0.0736
	+/-1	-0.0863	-0.2634***	-0.0513	0.1908	0.0892
	+/-3	-0.0916	-0.1793**	-0.1921	0.1838	-0.0135
β_{UA}	Strict	-0.0961	-0.1548	-0.2100	0.1289	0.0998
	+/-1	-0.0163	-0.0464	-0.1565	0.0963	0.1114
	+/-3	-0.0598	-0.1107	-0.1316	0.1214	0.1728
β_{DA}	Strict	0.0116	-0.0686	-0.0155	0.2817***	0.1011
	+/-1	0.0224	-0.1173	0.0344	0.2210**	0.1959
	+/-3	0.0638	-0.0530	0.0606	0.2165**	0.2104
R^2 adjusted	Strict	0.3277	3.5593	1.6724	3.0186	1.5128
	+/-1	0.1107	3.5256	1.8194	3.6445	2.4741
	+/-3	0.5923	3.7453	3.3256	3.9908	3.3041

Note: The table shows the impact on volume before and after a psychological price when prices are in a bullish or bearish market. UB is a dummy variable which takes value 1 during the 3 days before a psychological price is touched if the market is bullish and 0 otherwise, DB will take value 1 during the 3 days before reaching the psychological price if the market is bearish and 0 otherwise, UA will take value 1 during the 3 days after reaching a psychological price if the market before the price touches the barrier has been bullish and 0 otherwise, and DA will be equal to 1 during the 3 days if the market before the price touches the barrier has been bearish. In Panel A are shown the results for Level 0 and in Panel B we can find the results for Level 1. ***, ** and * indicate significance at 1%, 5% and 10%, respectively. R^2 adjusted is expressed in percentage.

Figure 1. Evolution of the price of the EUA December futures contracts



Note: Figure 1 draws the historical evolution of the price of the EUA ECX December futures contracts in Phase II from 18 December 2007 to 17 December 2012. The sample used contains intraday prices and all the December maturities of Phase II are included to build the continuous front contract series.

Figure 2. Distribution of the M values

Figure 2a. Distribution of the M values at level 0

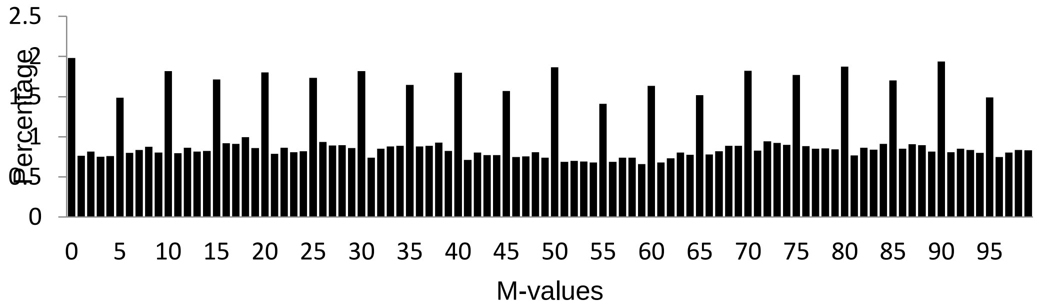
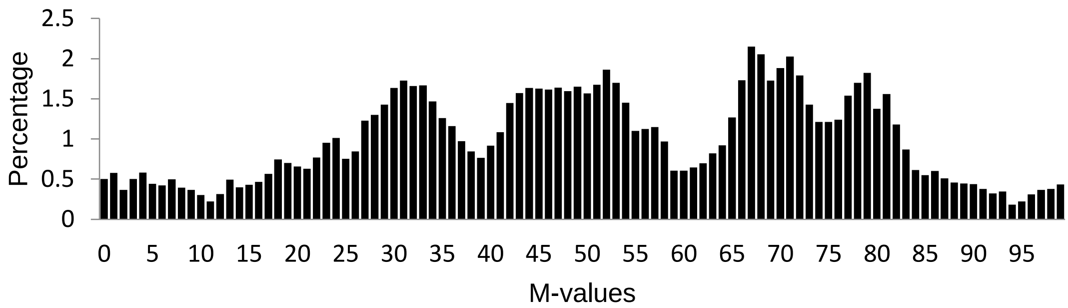
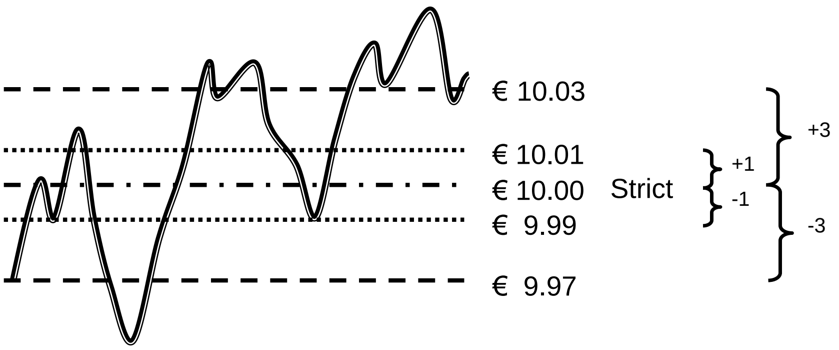


Figure 2b. Distribution of the M values at level 1



Note: Figure 2a shows the empirical distribution of the M-values at level 0, which is the decimal part of the price. Figure 2b shows the empirical distribution of the M-values at level 1, which considers the pair of the unit and the first decimal of the price.

Figure 3. Example of barrier bands around a barrier level



Note: Figure 3 shows a graphical example of the three regions in which we can consider that the price can be a psychological barrier. The three ranges are if the price is exactly the barrier (strict), and +/-1 and +/-3 M-values around the barrier level.

Figure 4. Distribution of the futures options

Figure 4a. Distribution of the futures options by trades

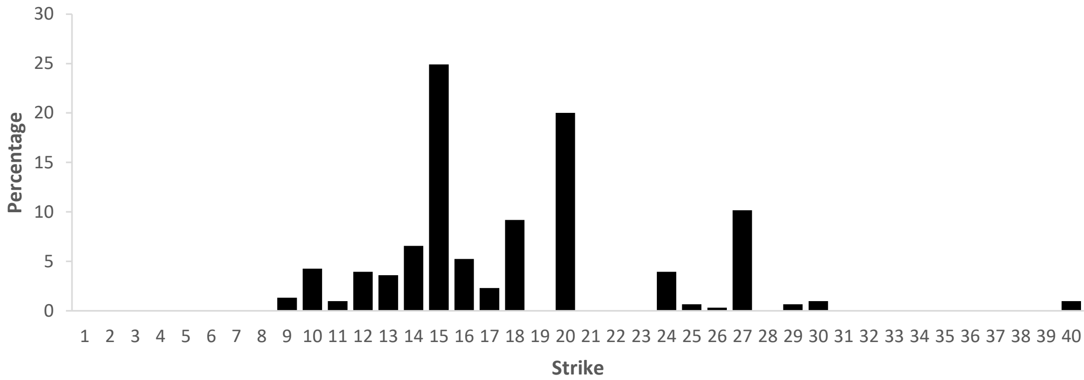
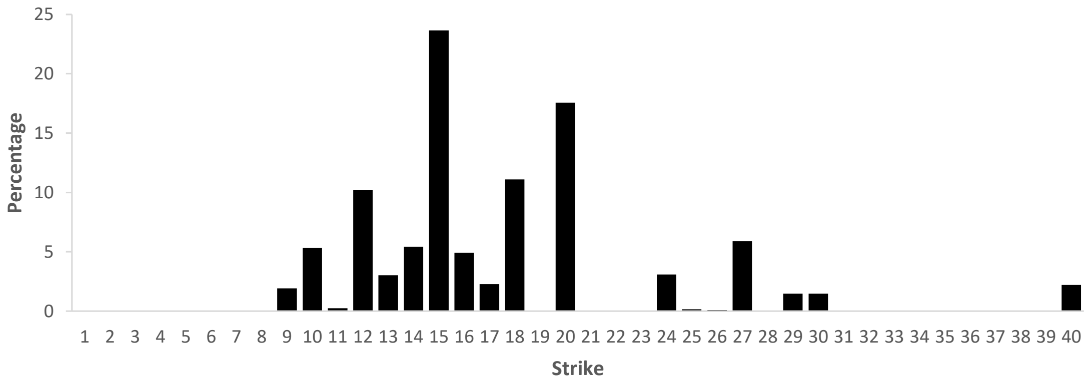


Figure 4b. Distribution of the futures options by volume



Note: Figure 4a shows the empirical distribution of the futures options by number of trades at each strike price. Figure 4b shows the empirical distribution of the futures options by the total volume traded at each strike price.

Chapter IV

DO CARBON TRADERS BEHAVE AS A HERD?

1. Introduction

In a general sense, herding can be defined as the act of placing together individual animals into a group with the intention of guiding them from place to place. Although herding is commonly used to describe animal behavior, we can also find herding behavior in humans that affects the decision-making process in fields like finance. Herding in finance is interpreted as the tendency of investors to mimic the actions of other investors. Specifically, Avery and Zemsky (1998) define herding in financial markets as a switch in the opinion of traders to the direction of the crowd. According to Spyrou (2013), market participants may infer information from the actions of previous participants and investors may react to the arrival of fundamental information. Therefore, someone in the market who knew about the existence of the herding effect and started to see early signs of a herding process occurring might place orders to take advantage of the effect and to better place his orders on the expectation that the trend was going to continue, with the aim of closing his positions before the current run ended.

In the literature on herding, we find two views of the phenomenon: irrational or rational.[24] The first one, also known as intentional herding, is mainly focused on psychology where people follow one another with the intention of copying the same decisions. This type of behavior can destabilize the market due to massive buys or sells increasing volatility and contributing to bubbles or financial crashes. The second view of herding is the rational or spurious herding that happens when investors react at the same time to certain market conditions or to the arrival of information. Devenow and Welch (1996) identify three causes for the existence

[24] See Devenow and Welch (1996), Bikhchandani and Sharma (2001), Spyrou (2013), and Galariotis, Rong and Spyrou (2015), among others, for comprehensive reviews of the financial literature on herding.

of rational herding: The first one makes reference to payoff externalities, in the sense that investors decide to imitate decisions taken by other agents in order to ensure their remuneration. The second one points to principal-agent problems where agents decide to follow or lead the herd due to reputational conditions. Finally, the third reason for the existence of rational herding is based on the existence of information cascades. The idea is that agents obtain useful information by observing the decisions of previous agents, to the point that they decide to refuse to use their own information on the belief that there are some other investors that are better informed, and they decide to act similarly. This last explanation is the most popular among researchers. In fact, Bikhchandani, Hirshleifer, and Welch (1992) and Welch (1992) show that following the decisions of other investors can be optimal because these previous agents have better information and, as a consequence, followers reject their private information.

Galariotis, Rong and Spyrou (2015) make an empirical literature review about the studies related to the herding effect and classify the studies into two categories that deal with the empirical tools employed to examine herd behavior in financial markets. The first group is composed of those methodologies that aim to detect institutional investor and analyst herding using micro-data, while the second group of methodologies investigates herding towards the market average and relies on aggregate market data. Kodres and Pritsker (1996), unlike the two categories of empirical works that are based on equity markets, examine whether large institutions herd in financial futures markets. They detect statistically significant herding among some classes of institutions in several futures contracts using daily position data. Specifically, their data consist of positions reported by the Commodity Futures Trading Commission as part of the large trader reporting system in which those market participants with a closing position at the end of the trading session above the threshold established for each futures contract must report their position.

Although we are not aware of any studies about herding in the European Carbon Market, there are several papers that have studied other behavioural aspects of this market. Palao and Pardo (2012, 2014) observed that carbon traders tend to concentrate their orders in transaction prices ending in 0 and 5 and in sizes of 1 to 5 contracts and in multiples of 5. Furthermore, they demonstrate that more clustered prices have more clustered sizes. Crossland, Li and Roca (2013) study momentum investment strategies in the European Carbon Market. These strategies are based on buying those assets that in the past have been winners and selling those that in the past have been losers. They detect short-term momentum and medium-term overreaction strategies that remain achievable after taking into account transaction costs. Chau, Kuo and Shi (2015) analyze whether carbon traders buy (sell) after a price rise and sell (buy) after a price fall. They do not find any significant feedback trading in emissions markets and their explanation is that the vast majority of investors in the carbon market are institutions that are less susceptible to behaviorally biased trading than retail investors. Finally, Palao and Pardo (2017) detect the existence of psychological prices that act as resistance or support levels in the EUA price and show that intraday volatility is greater before a barrier has been reached and decreases after touching it.

This chapter follows the line of research of Kodres and Pritsker (1996) and adds new evidence to the scarce literature on herding in futures markets. Specifically, we study the existence of herding behavior in the European Futures Carbon

Market by using an intraday trade database that allows us to study herding trends at high frequencies while distinguishing, at the same time, if the trade that provokes the run is buyer or seller initiated.

The European Futures Carbon Market is characterized by being highly dominated by professional market participants with presumably extensive financial training and, as a consequence, it is supposed that psychological influences on their trading strategies should play a limited role. In fact, Patterson and Sharma (2005, 2007) argue that the reason why many previous studies in the literature on herding do not find any effect is due to the analyses only focusing on the behavior of professional traders or institutional investors. Furthermore, given that this market is blind, the trading positions are not made available to other market participants, and this fact should make the likelihood of finding herding behavior even more difficult.

The remainder of this chapter is organized as follows. Section 2 describes briefly the European Carbon Market and the data used to perform this study. Section 3 applies the theory of runs to test the existence of the herding effect. Section 4 measures the herding effect and detects some herding patterns. Section 5, based on previous empirical papers on herding, investigates possible market drivers that can affect herding formation and, additionally, analyzes if herding destabilizes the carbon market. Finally, section 6 summarizes and concludes.

2. Market and data description

The European Commission launched in 2005 the European Union Emission Trading System (EU ETS). The aim of the scheme created under the Directive 2003/87/EC was to establish a multinational system, now formed by the 28 member countries and the three countries of the European Economic Area (EEA), Iceland, Liechtenstein and Norway, which cover around 45% of the Greenhouse Gases (GHGs) emitted by the countries included in the system. The EU ETS, with more than 12,000 installations covered by the scheme, is the world's largest emissions market in terms of installations covered and volume traded.

The EU ETS is a cap and trade system, where the limit of GHGs that can be emitted is fixed. This limit is reduced each year for the purpose of achieving the objective of emitting 21% less GHGs in 2020 than in 2005, which means a reduction of 1.74% per year. Installations participating in the EU ETS must monitor and report their emissions for each calendar year, and by 30 April of the following year each company must surrender enough allowances (known as European Union Allowances, or EUAs) to cover all its emissions. Otherwise, they will suffer a non-compliance penalty and heavy fines will be imposed.

The EU ETS is organized into trading periods or Phases. Phase I took place between 2005 and 2007 and is known as the pilot period where the main objective was having an emissions market fully operative when the Kyoto Protocol commitment started. Phase II occurred in the same period as the Kyoto Protocol emissions commitment which ran from 2008 to 2012. With the start of Phase II, a number of changes were incorporated into the program: the inclusion of additional GHGs, the incorporation of the three EAA states into the EU ETS, and the possibility of banking and borrowing.[25] Phase II was characterized by the plummet of the price of EUAs that fell from its maximum price due to a large

[25] Banking refers to the possibility of using allowances of the present period in the following one and borrowing is just the opposite, using allowances of futures periods to surrender current emissions requirements. Borrowing is allowed only in the same phase while banking is allowed both in the same phase and between phases.

surplus of allowances that can mainly be explained both by the economic crisis that took place during this period and the over-allocation of EUAs inherited from Phase I.

Phase III goes from 2013 to 2020 and additional significant changes have been introduced into the scheme. From this phase on, there is one single cap for all the countries that take part in the EU ETS, instead of the National Allocation Plan (NAP) system used in the previous phases. Moreover, the grandfathering system is being gradually abandoned. In 2013, more than 40% of the allowances were auctioned. Furthermore, some new sectors, such as petrochemicals and gas, have been incorporated into the program. Finally, Phase IV is scheduled to run from 2021 to 2030.

The European Commission is implementing several aspects to improve the functionality of the EU ETS. Particularly, the efforts are focused on trying to solve the problem of the surplus of allowances that at the start of Phase III was estimated at more than 2.1 billion allowances. In the short term, the Commission has applied so called “back-loading”, which means delaying the auctioning of 900 million allowances until the period 2019-2020, thereby reducing the volume that should be auctioned during the years 2014, 2015 and 2016 by 400, 300 and 200 million allowances, respectively. The idea is to increase the demand for credits during these years without affecting the total number of allowances that will be auctioned during Phase III. These allowances will be placed in the Market Stability Reserve (MSR). The MSR is a long-term measure developed by the European Commission which will be established in 2018 and operate from 1 January 2019. The MSR is a rule-based mechanism through which the auction volumes are adjusted in an "automatic manner" under pre-defined conditions that reduce the amount of EUAs that are auctioned if an upper threshold of EUAs in circulation is exceeded, and releases them if the EUAs in circulation fall short of a lower threshold.

EUAs can be traded in different platforms. For our analysis we have employed data from ICE Futures Europe, which is the reference market for trading carbon emissions in Europe. In this platform, the three most important futures contracts of the EU ETS are traded: EU Allowances (EUAs), EU Aviation Allowances (EUAAs) and Certified Emission Reductions (CERs). There are contracts with monthly and quarterly maturities, however the benchmark of the market is the annual contract which expiries the last Monday of December. Therefore, we have chosen the ICE EUA December futures contract as the reference for the price of the EUA.

Table 1 shows the evolution of the ICE EUA December futures contract in terms of volume of euros negotiated, number of contracts, and the average price in €/tonne traded each calendar year. As can be seen, in spite of the decrease in the EUA average price, the yearly trading volume has increased dramatically since Phase I.

ICE Futures Europe operates an electronic order-driven market with market makers and brokers. The transactions take place on a blind broker basis, that is, neither the buyer nor the seller knows their counterparties. The daily session starts with a pre-open period of 15 minutes (from 6:45 a.m. UK local time) to enable market members to input orders in readiness for the beginning of trading. The pre-trading period finishes with a single call auction, where the opening price and the allocated volume are determined by an algorithm. During the continuous session, from 7:00 to 17:00, investors can submit limit orders, market orders, and block orders. The futures market runs from 16:50:00 – 16:59:59 UK local time for the purpose of determining the settlement price, which is the weighted average during this period. The future contracts are traded in lots. Each lot equals 1,000 tonnes of CO_2 equivalent, that is, 1,000 EUAs. The minimum tick size is €0.01.

The sample we have used goes from December 18, 2012 to December 31, 2015. All the maturities belong to Phase III ICE EUA December futures contracts and the series contain the time stamp, the price, the size and the sign of the transaction (buyer or seller initiated), for all the trades that took place during the chosen period where a total of 1,214,304 transactions were made.

3. Runs test

One intuitive way of analyzing the presence of herding behavior in the ICE futures market is to study the evolution of the sign of the EUA price changes. Whether herding is intentional or unintentional, we should be able to observe a succession of trades that form an upward or downward trend in price changes. Following Gibbons and Chakraborti (2003, p.76), a run is defined as a succession of one or more types of symbols which are followed or preceded by a different symbol or no symbol at all. For instance, an up (down) run is created when the price of the EUA futures contract increases (decreases) consecutively until the price changes in the opposite direction. At this point, it is important to highlight that Palao and Pardo (2017) show the existence of psychological barriers in the EUA prices. They observe that once the price has touched a key level, EUA prices remain around it or rebound in the opposite direction. For this reason, we have also studied runs that allow not only ups or downs in prices but also their repetition. Therefore, we have followed two dichotomization criteria. A first one that separates the observations of the original sample between sequences of positive price changes (*Up*) and negative price changes (*Down*), and a second criterion that distinguishes sequences of positive price changes allowing price repetitions (*Zero&Up*) from sequences of negative price changes allowing price repetitions (*Zero&Down*).

Next, we have performed a test for randomness that is based on the total number of runs (R) in an ordered sequence of n elements of two types, n_1 elements of type 1 and n_2 elements of type 2. If the null hypothesis of randomness applies, the distribution of the statistic will follow a normal distribution with the following mean and variance:

$$\mu = \frac{2n_1n_2}{n_1+n_2} + 1,\ \sigma^2 = \frac{2n_1n_2(2n_1n_2-n_1-n_2)}{(n_1+n_2)^2(n_1+n_2-1)}\ .$$

The Z statistic is calculated as:

$$Z = \frac{R + c - \mu}{\sigma}$$

where R is the sum of the observed number of runs of type 1 and runs of type 2, and c is 0.5 if $R < \mu$ and -0.5 otherwise. At this point, it is important to note that the null hypothesis of randomness can be rejected if the total number of runs is too large or too small.

The results are shown in Table 2. Panel A shows the results where the run is created independently of who initiates the order that originates the sequence, which we have called the *General Case*. Panel B and C present the results taking into account whether the run is buyer or seller initiated, respectively. In each panel we include the number of observations, the number of runs for each type, and the statistic Z that follows a standardized normal distribution. The three panels show similar results and all Z values indicate the rejection of the null hypothesis at the 1% level. However, the lack of randomness when we compare sequences of positive and negative changes (*Up* vs *Down*) in all the panels is due to the large number of runs, while when we take into account the possibility of sequences with repetitions in prices (*Zero&Up* versus *Zero&Down*) the null is rejected because of the existence of too few runs. This is also the case when we study the randomness of buyer vs seller initiated runs (see the last row in Panel A). It is interesting to note that although there are many more observations of buyer initiated trades than seller initiated ones, the number of runs is quite similar.[26]

All in all, the above findings indicate that a certain level of herding behavior is present in the European Futures Carbon Market.

The reduction in the number of runs when we introduce the possibility of repetition of prices (see Panel A in Table 2) provokes an increase in the lengths of the runs. This feature can also be observed in Table 3 that shows the weighted percentage of occurrence of the lengths of each run per day. In each case runs are grouped using two scenarios: the first one, in which we have split the sample when the price increases, stays the same or decreases, and the second one, where we allow the repetition of prices.

[Insert here Table 3]

Panel A in Table 3 shows the results for the general case. We observe that sequences with a length of 1 run are the most frequent, 65% for the first scenario

[26] This result is contrary to that observed both by Wermers (1999) and Zhou and Lai (2009) that suggest that sell-herding is much more frequent that buy-side herding for equity markets.

and 32% in the second scenario. We also observe that the cases of up and down are quite similar in the first scenario, representing about 60% of the total runs, in which successions with a length of 1 run comprise 55% and the remaining lengths around 5%. Alternatively, in the second scenario, when we take together zeros with ups and downs, we observe higher frequency in larger runs, in fact, more than 20% of the total sequences have a length equal to or higher than 10. Therefore, as we expected, when we consider runs that allow for the repetition of prices, the presence of herding strengthens.

Panel B presents the results for buyer initiated runs. The upward movements are most frequent in the first scenario and the majority of the up runs are with a length of 1, representing 38%. For the whole sample, up runs make up 40% and downward runs only 9%. The second scenario shows a similar pattern as in Panel A but with an overall weight of Zero&Up runs of 64%. Finally Panel C displays the results for seller initiated runs. We can see just the opposite patterns to those detected in Panel B, with the highest frequency in downward runs (66%).

The fact that we observe downward runs when the buyer has initiated the run or upward runs when the initiator of the run is the seller indicates that runs can take any sign independently of who has initiated the run.

4. Herding measures and patterns

4.1. Herding measures

Several herding measures have been used in the literature on herding, mainly in equity markets. One of the most common herding measures is the so-called Cross-Sectional Standard Deviation, first used by Chang, Cheng and Khorana (2000). This measure is based on the comparison of asset returns with respect to the market return. Another widely applied statistic is that proposed by Lakonishok, Sheifer and Vishny (1992). This measure considers herding as the tendency of market participants to accumulate on the same side of the market in a specific stock and at the same time. This measure is calculated as the difference between the number of investors who buy (sell) a security in a time frame against their theoretical values.

The above mentioned measures have some features in common. They analyze the existence of herding in equity markets by employing a cross-sectional analysis, they require low frequency data –from daily to quarterly data– and, furthermore, they are able to detect herding only under extreme market conditions. These characteristics do not fit with our objectives. We are interesting in analyzing the evolution of daily herding behavior in a futures market, and under any market conditions, not necessarily extreme ones. For all these reasons, we have chosen the Herding Intensity measure proposed by Patterson and Sharma (2006). Following Simões Veira and Valente Pereira (2015), this method captures intraday order sequences, considered to offer the ideal frequency for testing the presence of herding behavior.

The statistic proposed by Patterson and Sharma (2006) is based on the information cascades model. These cascades take place when runs from buyer or seller initiated transactions last longer than would be expected if market participants had used their own information. The expression that measures the Herding Intensity is:

$$HI_{s,t} = \frac{x_{s,t}}{\sqrt{\sigma_{s,t}^2}}$$

The statistic $x_{s,t}$ is defined as follows:

$$x_{s,t} = \frac{\left(r_{s,t} + \frac{1}{2}\right) - n_t p_{s,t}(1 - p_{s,t})}{\sqrt{n_t}}$$

where $r_{s,t}$ is the number of runs of type *s* on day *t*, n_t is the total number of trades of each day and p_s is the probability of occurrence of a run of type *s*. Under asymptotic conditions, the statistic has a normal distribution with zero mean and variance:

$$\sigma_{s,t}^2 = p_{s,t}\left(1 - p_{s,t}\right) - 3p_{s,t}^2\left(1 - p_{s,t}\right)^2$$

In our case, we have considered 5 different type of runs: *Up, Zero, Down* and their combinations *Zero&Up* and *Zero&Down*. If herding does exist, the statistic of herding intensity should take significantly negative values, since the actual number of runs will be lower than expected. In this way, more negative values of the statistic will indicate higher herding intensity.[27]

4.2. Herding patterns

The next step is to analyze the evolution of the herding measure through time. However, based on previous empirical findings, we have decided to take into account some variables with the intention of capturing some seasonality patterns that could affect the level of herding behavior in the European Carbon Market. Firstly, following Chang *et al*. (2000) there is evidence of higher herding levels in emerging markets compared to developed ones. They attribute such higher levels to deficiencies in information quality that create uncertainty in the emerging

[27] This measure is applied, among others, for Blasco, Corredor and Ferreruela (2010, 2012) and Simões and Valente (2015) in their analysis about herding behavior in the Spanish and Portuguese stock market, respectively.

market. Simões Veira and Valente Pereira (2015) confirm this idea and indicate that almost all studies designed to detect herding behavior in developing stock markets and in relatively small illiquid capital markets found evidence of its existence. Therefore, it seems that herding is more likely to occur in less developed markets. To study this idea, we have included a variable *Trend* that counts the number of days of the sample.

Secondly, we also test if the herding intensity level changes through the year. Analyses performed by Klein (2013) and Galariotis *et al*. (2015) show that herding varies over time with a higher intensity in periods of turmoil. Regarding the European Carbon Market, Lucia, Mansanet-Bataller and Pardo (2015) show that the first quarter of the year is the period with the highest level of speculation. The rationale is that from the end of February, when companies receive their permits for the current year, till mid-May, when the EU Commission releases the report with the verified emissions, companies that know their real emissions can develop some trading strategies to try to exploit information not yet revealed to the market.

Thirdly, as we have previously mentioned, Palao and Pardo (2012) detect the strong presence of price clustering in the European Carbon Market at prices ending in digits 0 and 5. The existence of price clustering can alter the behavior of carbon traders, allowing traders to profit by posting orders before the quotation reaches a clustered price or by executing their limit orders at certain prices. Given that carbon traders concentrate their orders at these key prices, when the EUA trade prices arrive at these levels, the length of the runs will be longer than normal. Therefore, it is expected that more herding intensity will be observed on those days where the level of price clustering is abnormally higher.

Finally, according to Bikhchandani and Sharma (2001), reactions to public information is considered one of the possible causes of unintentional herding. Therefore, we have analyzed if the arrival of new public information to the European Carbon Market intensifies the level of herding among carbon traders.

All in all, to perform this analysis we deploy the following equation:

$$HI_{s,t} = \alpha + \beta_{Trend}Trend_t + \beta_{SP}Special\ Period_t + \beta_{PC}Price\ Clustering_t + \beta_{CN}Carbon\ News_t + \epsilon_{s,t}$$

where $Trend_t$ accounts for the number of days of the sample, $Special\ Period_t$ is a dummy variable that takes value 1 in the first quarter of the year and 0 otherwise, $Price\ Clustering_t$ is computed as the inverse of the normal cumulative standard frequency of prices ended in 0 or 5 for each day,[28] and $Carbon\ News_t$ is a dummy variable that that takes value 1 on days on which the European Commission makes public new information that affects the European Carbon Market and 0 otherwise.[29] Finally, $\epsilon_{s,t}$ are the residuals of equation for each type of run *s,* on day *t*.

We have run the equation using three different samples: the general case that takes into account all the trades independently of the sign of the trade and another two samples which are split by the initiator of the trade – buyer or seller[30]. In these three samples we will show five *s* scenarios: *Up, Zero, Down* and the

[28] In the study developed by Palao and Pardo (2012) the authors show that the inverse of normal cumulative standard frequency of prices ended in 0 or 5 for each day is a good proxy of price clustering.
[29] We have chosen this news about free allocation and leakage sector, market proposal reforms and estimations of realized emissions. All the chosen dates are reported in Annex I.
[30] We have also calculated the variable $Price\ Clustering_t$ for the three samples, all the data, buyer and seller initiated.

combinations *Zero&Up* and *Zero&Down*, each one of these scenarios belonging to one type of run.[31]

Table 4 presents the results. Panel A shows EU patterns for the general case that considers both buyer and seller initiated trades. First of all, the significance of the intercept and its negative coefficient confirms the existence of the herding effect in the five scenarios at the 1% level. The coefficient of the variable *Trend* is significant and positive suggesting that herding intensity decreases when the market is getting mature, probably due to the fact that carbon traders are more experienced. The coefficients β_{SP} and β_{PC} are also significant, but negative. The negative value for the first dummy indicates that carbon traders increase their herding behavior during the most speculative period that goes from January to March, while the negative coefficient for the second variable confirms that herding behavior is partially explained by the concentration of orders at the same price.

Finally, the negative and significant coefficient of the dummy β_{CN} indicates that the level of herding increases on those days on which important information is released by the EU Commission.

Note that the results for the five scenarios are very homogenous with values of adjusted R^2 around 20%. However, it is important to observe that all the coefficients are lower in the last two cases (*Zero&Up* and *Zero&Down*) in which the repetition of prices is allowed.

Looking at Panels B and C, we see two important differences depending on who initiates the run. Firstly, Panel B shows that the arrival of news that increases

[31] All regressions estimated in this study has been carried out using both ordinary least squares and the Newey and West correction that accounts for heteroskedasticity and serial correlation problems in the error terms in the models.

herding only has a slight influence in bearish scenarios, but not in bullish ones. Secondly, Panel C indicates that variable *Trend* is not significant, what means that the level of herding over time for sellers has remained the same. Furthermore, we notice that when runs are seller initiated, the arrival of carbon news always increases the level of herding.

5. Market drivers

Kremer and Nautz (2013) argue that the empirical literature on herding has explored its possible causes via the link between herding and information by considering variables that proxy the availability of information. Following this idea, we analyze in this section some factors that can influence carbon herding behavior.

Venezia, Nashikkar and Shapira (2011) analyze herding in the case of professional and amateur investors that trade in the Tel Aviv Stock Exchange and observe a positive and significant coefficient of the number of trades on the herding measure. They suggest that the factors leading to a greater intensity of trading also lead to a greater alignment of the traders' positions. In the same line, Grinblatt, Titman and Wermers (1995) also find a positive effect between the number of trades and herding behavior across mutual funds. Therefore, the first variable that we have considered is the trading frequency, defined as the number of daily trades.

The second variable that we have taken into account is daily volatility. According to Gleason, Mathur and Peterson (2004) and Tan, Chiang, Mason and Nelling (2008) people tend to herd more in situations with higher uncertainty. As it is commonly assumed in the financial literature, we associate higher levels of uncertainty with higher levels of volatility. Specifically, to measure intraday volatility, we employ the estimator proposed by Parkinson (1980) that is computed using the maximum and the minimum of each day. The expression is as follows:

$$\sigma_t = \sqrt{\frac{1}{4log2}(logH_t - logL_t)^2}$$

where H_t and L_t are the highest and the lowest EUA traded prices on day *t*, respectively.

The third market variable that we have considered is the time to maturity. Chiang, Li, Tan and Nelling (2013) suggest that the test for herding should consider its dynamic behavior. As the EUA futures contract nears its expiry, the amount of information available in the market would tend to be greater and the herding intensity measure should decrease. To explore if herding is time-varying, we have counted the number of days that remain to the expiry of each contract.

Finally, we have included the effect of extreme market returns on herding. Tan *et al.* (2008) observe that herding tends to be more intense during bull markets. Further, Chiang and Zheng (2010) point out that herding will be more prevalent during periods of market stress, defining market stress as periods of extreme returns. In order to analyze the impact of this variable on herding intensity, we have applied the methodology employed by Christie and Huang (1995), analyzing the impact of extreme returns with two dummy variables which indicate positive ($High_t$) and negative (Low_t) extreme returns that will take value 1 when returns are in the percentiles 95 and 5, respectively, and 0 otherwise.

The above-described variables have been regressed against the residuals of the EU patterns equation performed in the previous section. Therefore, the final structure of the market drivers' equation is as follows:

$$\epsilon_{s,t} = \alpha + \beta_{TF} \log(Trading\ Frequency_t) + \beta_V \sigma_t + \beta_{TTM} TTM_t + \beta_H High_t + \beta_L Low_t + \omega_{s,t}$$

Table 5 shows the regression output for the general case. We observe a positive relationship between herding intensity and trading frequency and volatility. The higher the trading frequency, the greater the carbon investors that are aligned to trade in the same direction. Regarding volatility, the higher the volatility, the higher the herding intensity measure, indicating that carbon traders herd more on riskier days. Furthermore, the coefficient that captures the vicinity of the futures contract is significantly positive, indicating that the fewer the number of days to the maturity of the EUA December futures contract, the higher the level of herding. Therefore, time to maturity has a positive influence on true behavior, reflecting an increase in the phenomenon at the end of the life of each futures contract. Finally, both extreme returns intensify herding behavior, especially when they are extremely negative. [32]

As we have seen, EUA volatility returns affects herding behavior in European carbon markets. However, there exists huge empirical evidence that the behavior of market agents can influence the volatility in stock markets.[33] Furthermore, the frequency analysis shown in Table 3 indicates that around 64.5% (66.2%) of

[32] This analysis has also been carried out both for buyer and seller initiated case, obtaining similar results. For the sake of space, these results have not been reported in the paper but are available upon request from the authors.

[33] As a consequence of this destabilizing effect, the classical market risk models would be underweighting the real market risk, as Morris and Shin (1999) and Persaud (2000) show. See Blasco, Corredor and Ferreruela (2012) for a comprehensive review of the impact of herding on volatility.

buyer (seller) initiated trades were *Zero&Up* (*Zero&Down*). If carbon traders buy after price increases or sell after price decreases, they can destabilize EUA market prices via herding behavior. In order to test if herding affects EUA volatility or market returns, we have regressed volatility (σ_t) and EUA return (R_t), defined as the first log-difference of the EUA carbon price series, against the daily herding intensity measure with 5 lags, as it appears in the following equations:

$$\sigma_t = \alpha + \sum_{l=1}^{5} \beta_{t-l} HI_{s,t-l} + \epsilon_{s,t}$$

$$R_t = \alpha + \sum_{l=1}^{5} \beta_{t-l} HI_{s,t-l} + \epsilon_{s,t}$$

Table 6 present the results. The coefficients of all the past measures of herding intensities that are significant are negative, indicating a positive relationship between volatility and returns and the level of herding. Although the effect of herding on EUA returns is weak (Panel B), its influence on EUA volatility lasts until the third lag at the 1% significance level (Panel A). This indicates that past EUA herding behavior leads to higher volatility.[34]

6. Conclusions

In this chapter we show for the first time the existence of the herding effect in the European Futures Carbon market, taking into account intraday data. Preliminary tests prove the presence of some herding behavior due to the lack of randomness in sequences of positive or negative changes in EUA prices. Additionally, and explained by the presence of EUA psychological barriers, we show that the length

[34] We have also run the same analysis for buyer and seller initiated trades with similar results. They are available upon request.

of the sequences increases markedly when we introduce the possibility of the repetition of prices that occurs when prices reach an EUA price barrier.

The EU patterns analysis confirms the existence of the herding effect, although its effect is diminishing over time. Furthermore, we observe that the herding level increases in speculative periods, on those days on which the price clustering effect is stronger, and with the arrival of new information. Regarding market drivers, we find that herding behavior is positively related with the number of trades, the intraday volatility and on days with extreme returns. On the contrary, herding is less intense when the EUA futures contracts reach their expiry. All these results appear to support the claim that the higher the availability of information, the lower the level of herding. Finally, we show that carbon volatility overreacts to past herding behavior, which means that the herding effect affects and is affected by carbon volatility.

The results obtained in this chapter should be of interest both to academics and to carbon practitioners. On one hand, we add new insights to the sparse literature on herding in futures markets and, on the other hand, we show that psychological influences can play an important role in trading strategies in the European Futures Carbon Market, in spite of it being a blind market that is highly dominated by skilled professional market participants.

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Annex: tables and figures

Table 1. EUA futures price and trading volume

Year	Negotiation (€)	# trades	Average price (€/t)
2005	974,830,550	4,389	22.69
2006	3,863,747,450	21,973	17.08
2007	11,482,898,690	84,727	17.62
2008	19,146,498,980	171,774	22.74
2009	23,002,292,760	318,981	13.60
2010	42,831,298,310	338,964	14.80
2011	43,673,216,110	394,131	13.33
2012	35,989,018,200	483,058	7.68
2013	24,694,339,700	553,316	4.59
2014	32,024,212,410	546,895	6.03
2015	27,969,042,380	390,618	7.71

Note. The table shows the negotiation in euros, the number of trades and the average price for each calendar year for December futures contracts. The last time the database was updated was December 31st, 2015. Source: ICE ECX and prepared by the authors.

Table 2. Runs tests

Panel A. General	n_1/n_2	r_1/r_2	Z
Up vs Down	130,909/129,636	121,388/119,911	435.0436
Zero&Up vs Zero&Down	618,055/596,246	87,017/86,984	-786.0479
Buyer vs Seller	636,415/577,889	109,513/109,564	-703.4147

Panel B. Buyer	n_1/n_2	r_1/r_2	Z
Up vs Down	107,742/24,303	101,325/23,425	779.6194
Zero&Up vs Zero&Down	487,008/149,404	95,538/52,447	-281.4627

Panel C. Seller	n_1/n_2	r_1/r_2	Z
Up vs Down	23,167/105,333	22,051/98,761	781.7753
Zero&Up vs Zero&Down	131,047/446,842	49,141/96,123	-215.2964

Note. Table 2 shows the results for runs tests where the null hypothesis is that elements of two different types of the same sample follow a random process. In the table are shown the number of observations of elements of type1 (n_1) and type 2 (n_2); the number of runs of type 1 (r_1) and type 2 (r_2), and the statistic Z that follows a normal distribution. Panel A shows the results for the general case, Panel B for buyer initiated runs, and Panel C for seller initiated runs. We have considered four types of sequences: *Up* for a sequence of positive price changes, *Down* for a sequence of negative price changes, *Zero&Up* for a sequence of positive price changes allowing price repetitions, and *Zero&Down* for a sequence of negative price changes allowing price repetitions.

Table 3. Frequency analysis

Panel A. General

Scenario #1	1	2	3	4	5	6	7	8	9	≥10	Total
Up	27.9234	1.9716	0.1578	0.0171	0.0035	0.0010	0.0002	0.0000	0.0000	0.0000	30.0747
Zero	10.1171	6.3993	4.5265	3.3737	2.5918	2.0864	1.6830	1.3604	1.1134	6.9649	40.2166
Down	27.5064	2.0249	0.1553	0.0168	0.0042	0.0007	0.0000	0.0000	0.0000	0.0002	29.7087
Total	65.5470	10.3959	4.8397	3.4076	2.5995	2.0881	1.6833	1.3604	1.1134	6.9652	100.00

Scenario #2	1	2	3	4	5	6	7	8	9	≥10	Total
Zero&Up	16.6792	7.0333	4.3178	3.0138	2.3626	1.8506	1.5937	1.3178	1.1345	10.7063	50.0095
Zero&Down	15.4298	7.4706	4.6092	3.3195	2.4373	2.0155	1.6638	1.3661	1.1718	10.5068	49.9905
Total	32.1090	14.5039	8.9270	6.3333	4.8000	3.8661	3.2575	2.6839	2.3063	21.2131	100.00

Panel B. Buyer

Scenario #1	1	2	3	4	5	6	7	8	9	≥10	Total
Up	38.5619	2.2246	0.1544	0.0170	0.0024	0.0000	0.0000	0.0000	0.0000	0.0000	40.9602
Zero	17.8539	9.1651	5.7168	3.8545	2.6721	1.9885	1.5333	1.1658	0.9176	4.7026	49.5703
Down	9.1440	0.3016	0.0198	0.0024	0.0016	0.0000	0.0000	0.0000	0.0000	0.0000	9.4695
Total	65.5598	11.6912	5.8911	3.8739	2.6761	1.9885	1.5333	1.1658	0.9176	4.7026	100.00

Scenario #2	1	2	3	4	5	6	7	8	9	≥10	Total
Zero&Up	22.9584	10.1625	6.5284	4.4829	3.3679	2.5651	2.1658	1.7137	1.3887	9.2259	64.5592
Zero&Down	17.5504	6.8723	3.6098	2.1218	1.3785	0.9001	0.6433	0.4318	0.3521	1.5806	35.4408
Total	40.5088	17.0348	10.1382	6.6047	4.7464	3.4652	2.8091	2.1455	1.7407	10.8065	100.00

Panel C. Seller

Scenario #1	1	2	3	4	5	6	7	8	9	≥10	Total
Up	8.7439	0.3737	0.0303	0.0054	0.0021	0.0004	0.0004	0.0000	0.0000	0.0000	9.1562
Zero	18.8704	9.5224	5.7276	3.8861	2.6641	1.9217	1.4130	1.0597	0.8313	3.9393	49.8356
Down	38.4932	2.3303	0.1632	0.0170	0.0042	0.0000	0.0000	0.0000	0.0000	0.0004	41.0083
Total	66.1075	12.2264	5.9211	3.9085	2.6703	1.9221	1.4134	1.0597	0.8313	3.9397	100.00

Scenario #2	1	2	3	4	5	6	7	8	9	≥10	Total
Zero&Up	17.4021	6.6624	3.3401	1.9434	1.2047	0.7903	0.5232	0.3862	0.2960	1.2804	33.8288
Zero&Down	23.2714	11.2471	7.1036	4.9193	3.5287	2.7701	2.0989	1.6859	1.3630	8.1830	66.1712
Total	40.6735	17.9095	10.4437	6.8627	4.7335	3.5604	2.6221	2.0721	1.6590	9.4635	100.00

Note. Table 3 shows the weighted percentage of occurrence of the length of each run for each scenario. Two scenarios are shown: the first one considers cases in which the prices rise, stay equal or fall, and the second one allows the repetition of prices. Panel A, B, and C show the result for the whole sample, only for buyer initiated trades and only for seller initiated trades, respectively.

Table 4. EU patterns

Panel A. General

	Up	*Zero*	*Down*	*Zero&Up*	*Zero&Down*
α	-102.6891***	-100.9300***	-102.8328***	-128.8311***	-128.8313***
β_{Trend}	0.0140**	0.0139**	0.0141**	0.0188**	0.0188**
β_{SP}	-18.0517***	-17.6767***	-18.0028***	-22.7015***	-22.6998***
β_{PC}	-20.2805***	-20.0913***	-20.2867***	-25.3968***	-25.3961***
β_{CN}	-10.6002**	-10.5476**	-10.5639***	-13.5263**	-13.5290**
Adjusted R^2	0.2007	0.1980	0.2003	0.2088	0.2088

Panel B. Buyer

	Up	*Zero*	*Down*	*Zero&Up*	*Zero&Down*
α	-70.5850***	-69.5802***	-76.1770***	-88.2703***	-91.3744***
β_{Trend}	0.0135***	0.0141***	0.0161***	0.0178***	0.0190***
β_{SP}	-9.6375***	-9.7489***	-10.6274***	-12.1756***	-13.0645***
β_{PC}	-11.3752***	-11.4931***	-11.9112***	-14.3923***	-14.6316***
β_{CN}	-5.4263	-5.5759	-6.4322*	-7.1839	-7.6555*
Adjusted R^2	0.1553	0.1628	0.1822	0.1653	0.1805

Panel C. Seller

	Up	*Zero*	*Down*	*Zero&Up*	*Zero&Down*
α	-68.6766***	-61.9295***	-62.9241***	-82.4546***	-78.1763***
β_{Trend}	0.0072	0.0045	0.0041	0.0084	0.0056
β_{SP}	-15.9767***	-15.4029***	-15.3471***	-19.3684***	-19.5469***
β_{PC}	-9.7979***	-9.8303***	-9.5964***	-12.0543***	-11.9899***
β_{CN}	-9.8354***	-9.4597***	-9.1026***	-12.0296***	-11.5323***
Adjusted R^2	0.1962	0.1827	0.1770	0.1937	0.1871

Note. Table 4 shows the impact of some EU patterns on herding intensity in five scenarios: Up, Zero, Down, Zero&Up and Zero&Down. These patterns are Trend, β_{Trend}, which accounts for the number of days of the sample, β_{SP} represents the variable Critical Period which is a dummy variable that takes value 1 in the first quarter of the year and 0 otherwise, β_{PC} is Price Clustering which is the inverse of normal cumulative standard frequency of prices ending in 0 or 5 for each day and, finally, Carbon News represented by β_{CN} which is a dummy variable that takes value 1 on those days when the EU Commission publishes new information important for the European Carbon Market. ***, ** and * indicate significance at 1%, 5% and 10% respectively. Panels A, B and C show results for the whole sample, and for buyer and seller initiated trades, respectively.

Table 5. Market drivers

	Up	*Zero*	*Down*	*Zero&Up*	*Zero&Down*
α	188.3601***	183.7694***	188.6774***	236.0069***	236.0338***
β_{TF}	-27.3876***	-26.7367***	-27.4294***	-34.2671***	-34.2710***
β_V	-109.0932**	-117.5602**	-109.9114**	-139.4668**	-139.4048**
β_{TTM}	0.1022***	0.1023***	0.1021***	0.1256***	0.1256***
β_H	-6.9044**	-6.8464**	-7.2288**	-8.7745**	-8.7713**
β_L	-8.1275**	-7.8130**	-7.5572**	-9.5523**	-9.5516**
Adjusted R^2	0.6066	0.5988	0.6059	0.6152	0.6153

Note. Table 5 shows the impact of some EU market drivers on herding intensity in five scenarios: Up, Zero, Down, Zero&Up and Zero&Down. The dependant variable is the residual of EU pattern estimation output and the market drivers are β_{TF} that accounts for the natural logarithm of the number of orders traded each day, β_V proxies the daily volatility, β_{TTM} is a dummy variable that accounts for the days remaining to the expiry and, finally, β_H and β_L both are dummy variables that take value 1 when the daily return is in the 95% and 5% percentiles, respectively and 0 otherwise. ***, ** and * indicate significance at 1%, 5% and 10% respectively.

Table 6. Market destabilization and herding behavior

Panel A. EUA Volatility

	Up	*Zero*	*Down*	*Zero&Up*	*Zero&Down*
α	-0.0179***	-0.0175***	-0.0177***	-0.0184***	-0.0184***
β_{t-1}	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0002
β_{t-2}	0.0000	0.0000	0.0000	0.0000	-0.0001***
β_{t-3}	-0.0001***	-0.0001***	-0.0001***	-0.0001***	-0.0001
β_{t-4}	-0.0001	-0.0001	-0.0001	0.0000	-0.0001***
β_{t-5}	-0.0001	-0.0001	-0.0001	0.0000	0.0000
Adjusted R^2	0.1535	0.1526	0.1526	0.1589	0.1589

Panel B. EUA Returns

	Up	*Zero*	*Down*	*Zero&Up*	*Zero&Down*
α	-0.0004	-0.0006	-0.0004	-0.0001	-0.0001
β_{t-1}	0.0000	0.0000	0.0000	0.0000	0.0000
β_{t-2}	-0.0002*	-0.0002*	-0.0002*	-0.0001*	-0.0001*
β_{t-3}	0.0001	0.0001	0.0001	0.0001	0.0001
β_{t-4}	0.0001	0.0001	0.0001	0.0001	0.0001
β_{t-5}	0.0000	0.0000	0.0000	0.0000	0.0000
Adjusted R^2	0.0031	0.0030	0.0026	0.0031	0.0031

Note. The table shows the estimation output of the linear regression of the volatility and returns against the herding intensity using as independent variables the herding intensity measure lagged from 1 to 5 days. Panel A shows the results for volatility while Panel B shows the results for returns. The study has been carried out for the five scenarios: Up, Zero, Down, Zero&Up and Zero&Down. ***, ** and * indicate significance at 1%, 5% and 10%, respectively

Annex I. Market news

Date	Description
24/01/2013	Linking EU ETS with Australia: Commission recommends opening formal negotiations
25/01/2013	Free allocation of allowances in 2013
30/01/2013	Consultation meetings on the options for structural measures to strengthen the EU Emissions Trading ...
05/03/2013	Consultation on registry options to facilitate linking of Australian and EU emissions trading systems
16/04/2013	Commission reacts to European Parliament back-loading vote
16/05/2013	EU ETS: continuing decline in emissions but growing surplus of allowances in 2012
06/06/2013	Stakeholder consultation on new carbon leakage list launched
18/06/2013	Member States approve EEX as Germany's phase 3 auction platform
03/07/2013	Commission welcomes EP vote on ETS 'backloading'
10/07/2013	Member States approve addition of sectors to the carbon leakage list for 2014
05/09/2013	Commission finalizing decision on industrial free allocation for phase three
05/09/2013	Commission clears way for harmonized free allocation to industry for phase three
24/09/2013	Experts to explore one of the options for EU ETS structural measures
08/11/2013	Back-loading proposal takes step forward
11/12/2013	EU Climate Change Committee makes progress on back-loading
18/12/2013	Commission gives green light for a first set of Member States to allocate allowances for calendar year 2013
08/01/2014	EU Climate Change Committee agrees back-loading
26/02/2014	Commission gives green light for free allocation by all Member States
27/02/2014	Back-loading: 2014 auction volume reduced by 400 million allowances
05/05/2014	Commission submits proposed carbon leakage list for 2015-2019
14/05/2014	EU ETS emissions estimated down at least 3% in 2013
16/05/2014	Commission to hear experts on technical aspects of proposed market stability reserve
04/07/2014	Commission publishes first status update for New Entrants' Reserve (NER) and impact of cessation rules
09/07/2014	EU Climate Change Committee agrees proposed carbon leakage list for the period 2015-2019
16/07/2014	European Securities and Markets Authority launches consultation on the implementation of new financial markets rules that are relevant for EU ETS
27/10/2014	European Commission adopts the carbon leakage list for the period 2015-2019
10/02/2015	Aviation/ETS: Update of the aircraft operators list
23/07/2015	Commission publishes status update for New Entrants' Reserve and allocation reductions

Note. The table shows the dates selected as the most important for the European Carbon Market during Phase III and its description. Source EU Commission: http://ec.europa.eu/clima/consultations/index_en.htm

Conclusions

1. Conclusions

This PhD dissertation analyzes the influence of some behavioral aspects of trading participants over the European Carbon Market, more precisely in the European Union Allowance (EUA). Next are described the major and minor findings.

1.1. Major findings

I. We have proved the existence of price clustering in the European Carbon Market where prices ending tend to be concentrated at round numbers ended in 0 and 5.

II. There it exists a size clustering effect where carbon traders tend to cluster their orders in small sizes and in round numbers multiples of five contracts.

III. We have shown the existence of key prices that modifies the behavior of carbon market actors, explained both by the existence of price clustering effect and rounded exercise prices in EUA options.

IV. In this study we show for first time the existence of the herding effect in the European Futures Carbon Market despite of being a blind market and dominated by professional participants.

1.2. Minor findings

I. Price clustering effect is greater when the lack of information is higher in the market, higher volatility and less trading frequency.

II. Our analysis also shows that price and size resolution in the European Carbon Market are complementary so that carbon traders place orders rounding both, price and size.

III. The presence of key prices affects to volatility increasing it before touching the barrier and decreases after it. Also returns and volume dynamics are modified with the existence of psychological prices ended in zero rounded prices.

IV. A pattern analysis shows that herding is intesified with the level of speculation and other behavioral biases like psychological prices or price clustering.

2. Further research

The study carried out in the dissertation of this doctoral thesis has explored the influence of behavioral finance over the European Carbon Market, but this work should be considered as a starting point in the study of how human behavior influences in the emissions market.

As it has been said, the study developed in Chapter III is the first are in assessing the impact of technical analysis over the European Carbon Market. This work can be extended with the analysis of other common technical analysis tools such as moving averages or Bollinger bands. Furthermore, it will be useful for this type of analysis to develop a method to determine the most suitable time horizon to analyze the right psychological price in each period and analyzing all of these studies in an intraday level.

Chapter IV could be extended in two different ways, the first one is related to the analysis of herding in sizes instead of prices. Preliminary showed that the first trade of a run is statistically significant greater than the rest of the run. Moreover, the study of the level of autocorrelation in volume can offer new insights in terms of developing trading strategies that allows to take better positions in terms of price and time. The second approach of herding is based in the study of herding among market data providers and exchanges. It is of interest to know if the main market data providers and exchanges make public price transactions at the same time and if these prices are equal, or in contrast, if it exists a leader that is the first one in providing new changes in the quotation and the others follow him. This information is quite relevant when choosing the exchange to trade and/or the market data provider to have the most updated information.

Additionally, a common further line of research that could be applied for all the chapters is the study of the predictive power of the detected anomalies by analyzing the profitability of several trading strategies with out-of-sample data. To this end, it would be necessary to establish the rules that define when to enter into the carbon market or to exit from it.

Alternatively, one of the proposals of European Commission to improve the European Union Emission Trading System, is to establish a soft price corridor or collar to the EUA price. The supporters of the establishment a price collar argue that the measure will give more stability to the market, also those companies that invest in low carbon technologies would see reduced the risk of invest in these type of installations. The introduction of a price floor will also aim many industries covered by the program to trigger to low carbon investments.

This price floor will be controlled through auctions, if the auction price is below the low threshold the auction will be canceled and the allowances will be placed in the reserve until the price reach the upper threshold. Furthermore, this minimum price for the EUA will evolve yearly with a predetermined path. The introduction of this new measure in the EU ETS can motivate new studies about the behavior of carbon market participants, such as, the use of options with strike price in the floor price on the auction days. Furthermore, we could interpret this collar like psychological barriers, so we could analyze the investor behavior when the price is near to these upper or lower threshold.

Resumen

1. Introducción

Puesto que ninguno de los cuatro capítulos que forman parte de esta tesis está escrito en algunas de las dos lenguas oficiales de la Universidad de Valencia, en cumplimiento de su normativa, a continuación se resume en castellano dicha tesis doctoral describiendo el campo de estudio, los datos empleados, el objetivo y la metodología y los resultados y las conclusiones que se derivan de ella.

1.1. Finanzas del comportamiento

Esta tesis se enmarca dentro del campo de las finanzas del comportamiento, el cual propone teorías basadas en la psicología y la sociología con el fin de explicar algunas anomalías observadas en los mercados financieros.

Las finanzas del comportamiento tratan de llenar el hueco de los modelos financieros clásicos, basados en mercados plenamente eficientes donde todos los agentes interactúan de forma racional entre ellos, y que muchas veces se han mostrado incapaces de explicar matemáticamente algunos aspectos del comportamiento del mercado.

En concreto, esta tesis se centra en el análisis de cuatro sesgos observados en los mercados financieros. El primero sería la agrupación en precios, el cual puede ser definido como la tendencia a observar ciertos precios negociados más frecuentemente que otros, este fenómeno puede afectar a la parte decimal del precio, a la parte entera o a ambos. Siguiendo la Teoría de los Mercados Eficientes, en ausencia de fricciones en el mercado, los precios en cualquier situación deberían estar uniformemente distribuidos a través de cualquier precio puesto que todos los precios tienen la misma probabilidad teórica de poder ser negociados y, por tanto, la presencia de una agrupación en los precios de las transacciones realizadas es considerada como una fuente de ineficiencia de mercado debido a que los precios no seguirían un paseo aleatorio.

El segundo aspecto analizado en esta tesis tiene que ver con la agrupación en tamaños, esto es, la concentración de órdenes en determinados tamaños de negociación. La presencia de esta anomalía afectaría a la liquidez del activo puesto que podría dificultar a los inversores la negociación de las posiciones deseadas, viéndose penalizados tanto en precio, teniendo que negociar a niveles más profundos del libro de órdenes, como en tiempo, teniendo que esperar más tiempo para poder negociar el número de activos o contratos deseados al precio objetivo.

Son cuatro las teorías las que parecen explicar la agrupación en precios y tamaños. En primer lugar estaría la *hipótesis de resolución*, la cual establece que la presencia de incertidumbre lleva a los participantes del mercado a redondear tanto el precio como el tamaño a negociar. En segundo lugar se encontraría la *hipótesis de atracción* que sugiere que los inversores prefieren ciertos números sobre otros sin ninguna explicación racional. En tercer lugar, la *hipótesis de la negociación* establece que la agrupación en precios y en tamaños ocurre por una cuestión de conveniencia a la hora de negociar los activos en el mercado. El inversor utilizaría un reducido grupo de valores con el fin de reducir los costes de negociación ya que de este modo la información que tendría que ser procesada por los agentes sería menor y podrían llegar a acuerdos más fácilmente. Por último, la *hipótesis de colusión* sugiere que los creadores de mercado podrían intentar negociar determinados precios y tamaños de órdenes solo para incrementar las ganancias por los márgenes de las transacciones.

Otros sesgo psicológico que aparece con frecuencia tanto en los agentes que negocian en el mercado como en los medios que se encargan de informar sobre dichos mercados es la existencia de barreras psicológicas. Este fenómeno, al igual que el efecto agrupación, hace que los participantes del mercado confieran una importancia especial a determinados precios sobre otros, creando así un impedimento mental en los individuos que causa un cambio sus decisiones de negociación cuando la cotización del activo se acerca dichas barreras psicológicas.

El fenómeno de las barreras psicológicas, también llamadas precios barrera o precios clave, ha sido tratado con anterioridad en la literatura financiera la cual ha sugerido varias explicaciones posibles para la aparición de dicho efecto. La primera teoría relaciona las barreras con el concepto de anclaje, esta teoría sugiere que los individuos se fijan en un precio reciente para posicionar sus órdenes que podría prevalecer como importante para los analistas del mercado. La segunda teoría está relacionada con el ya descrito efecto agrupación en la *hipótesis de la negociación*, el cual indica que los inversores tienden a redondear los precios para simplificar su proceso de negociación lo cual les otorga una importancia superior al resto. Finalmente, la tercera explicación del efecto de las barreras psicológicas está relacionada con la existencia de determinados precios clave que facilitan la posibilidad de hacer coberturas con contratos de opciones, dado que las opciones son comúnmente negociadas con precios de ejercicio estándar que aparecen propuestos en las condiciones generales de los contratos.

Finalmente, el último aspecto psicológico que estudiaremos es el llamado efecto imitación. Este efecto, comúnmente asociado con el comportamiento animal de ir en manada o en un rebaño, es usado también en finanzas para definir la tendencia de los inversores a imitar las acciones de otros inversores.

Este efecto gregario puede ser visto desde dos puntos de vista: racional e irracional. La primera visión contempla el efecto imitación como una reacción del mercado a la llegada de nueva información que afecta al mercado, lo cual, estaría en línea con la Teoría de los Mercados Eficientes. El segundo punto de vista, también conocido como efecto gregario intencional, esta principalmente centrado en la psicología, donde los agentes se siguen unos a los otros con la intención de copiar la misma decisión. Algunas razones que justificarían tal comportamiento pueden ser la existencia de recompensas por batir un determinado índice, los problemas de agencia o la existencia de cascadas de información. Este tipo de comportamiento gregario intencional puede desestabilizar el mercado debido a compras o ventas masivas que incrementan la volatilidad y que pueden contribuir a la creación de burbujas o de quiebras financieras.

1.2. El Mercado Europeo de Carbono

El Mercado Europeo de Carbono es el principal instrumento de la política climática europea a la hora de evitar el incremento de emisiones de gases de efecto invernadero y fue creado en enero de 2005 bajo la directiva 2003/87/EC. El Sistema Europeo de Intercambio de Emisiones es un sistema multinacional que cubre generadores eléctricos, industria pesada, industria intensiva en energía y las emisiones del sector aeronáutico de los 28 países miembros y los tres países del Área Económica Europea, Islandia, Liechtenstein y Noruega estando sujetas al programa más de 12.000 instalaciones que cubren alrededor del 45% de las emisiones de gas de la Unión Europea. Con estas cifras el

Sistema Europeo de Intercambio de Emisiones es el mayor mercado de emisiones tanto en términos de volumen de emisiones negociadas como en términos de instalaciones cubiertas.

El Sistema Europeo de Intercambio de Emisiones es un sistema basado en una negociación, donde se fija un límite o tope para determinar la cantidad total de gases de efecto invernadero que pueden ser emitidas. Este límite se reduce cada año, haciendo que de este modo la cantidad total de emisiones se reduzcan. Las instalaciones participantes en el programa están obligadas a monitorizar e informar de sus emisiones anuales y entregar el 30 de abril del año siguiente los suficientes derechos de emisión como para cubrir sus emisiones. En caso contrario, tendrán una penalización por incumplimiento y se les impondrá severas multas.

La vida del programa puede ser dividido en fases: Fase I desde 2005 a 2007, Fase II desde 2008 a 2012, Fase III desde 2013 a 2020 y Fase IV que tendrá lugar desde 2021 a 2030. El objetivo de reducción de emisiones es emitir en 2020 un 21% menos que en 2005, esto se traduce en una reducción anual de 1,74% para las Fases I a III y emitir un 43% menos en 2030 por lo que la reducción anual será de 2,2% durante esta fase.

La Fase I fue un periodo de prueba, cuyo principal objetivo fue establecer un mercado de emisiones totalmente operativo para el comienzo del Compromiso del Protocolo de Kyoto. En esta fase, cada país miembro elaboró un Plan Nacional de Asignación de emisiones que tuvo que ser aprobado por la Comisión Europea. Dado que fue la primera fase y los países no tenían datos creíbles sobre emisiones los límites fueron fijados basados en expectativas.

La Fase II transcurrió a la vez que el Compromiso del Protocolo de Kyoto. Durante esta fase nuevos gases de efecto invernadero fueron incorporados al programa, (óxido nitroso y perfluorocarbonos) y el número de países miembros del programa se incrementó con la incorporación de los estados del Área Económica Europea. Otro aspecto importante que se introdujo fue la posibilidad de usar derechos del periodo actual en el siguiente (*banking*) y justo lo contrario, usar derechos de periodos futuros para cubrir los requerimientos actuales de entrega de derechos de emisiones (*borrowing*). El uso de los derechos de periodos futuros está permitido solo dentro de la misma fase, mientras que los derechos que se guarden para ser entregados a futuro podrán utilizarse tanto en la fase a la que corresponden estos derechos como en fases posteriores.

A partir de la Fase III, los Planes Nacionales de Asignación son abandonados y desde esta fase se establece un solo límite de emisiones para todos los países miembros. Además, la libre asignación de los derechos de emisión a las instalaciones se redujo gradualmente. En 2013, más del 40% de las emisiones fueron subastadas. Por otro lado, durante esta fase la Comisión también centró sus esfuerzos en reducir el exceso de derechos de emisión implementando medidas en el corto plazo tales como un retraso en la subasta de 900 millones de derechos de los años 2014, 2015 y 2016 para ser subastados en 2019 y 2020. También se tiene previsto que comience a operar, en enero de 2019, la Reserva de Estabilidad del Mercado, un mecanismo regulado donde los volúmenes subastados son ajustados de una “forma automática” bajo condiciones predefinidas que reducen la cantidad de emisiones que son subastadas si un límite superior de emisiones en circulación es excedido, y liberadas si los derechos de emisiones en circulación bajan de un determinado umbral.

La propuesta para la Fase IV es reducir las emisiones a un nivel 43% inferior a 2005 con una reducción anual del 2,2%. Los esfuerzos también se centrarán en revisar el sistema de libre asignación de derechos reduciéndola a los cerca de 50 sectores con alto riesgo de relocalización de la producción fuera de la Unión Europea. Además, las referencias para la libre asignación de derechos de emisión serán actualizadas con el fin de reflejar los cambios tecnológicos acaecidos desde al año 2008.

El principal activo del Sistema Europeo de Intercambio de Emisiones es el derecho de emisión, el cual, da derecho a emitir una tonelada de CO_2 o gas equivalente. La evolución de la cotización del derecho de emisión se ha visto afectada principalmente por dos eventos acaecidos tanto en la primera como en la segunda fase. Al final de la Fase I, debido a la imposibilidad de usar los derechos sobrantes de la Fase I en la siguiente fase, el precio del derecho de emisión se hundió llegando a cotizar a 0 €. En la Fase II, estos problemas de exceso de derechos de emisión continuaron y, que junto con la crisis financiera, influyeron en una baja demanda de derechos de emisión. En conjunto, todos estos eventos, tanto de la Fase I como de la Fase II provocaron que el precio del derecho de emisión haya oscilado entre 0 € y 30 € desde 2006 a 2015.

1.3. El mercado ICE ECX

Actualmente existen cuatro plataformas que ofrecen la posibilidad de negociar contratos del Sistema de Comercio de Emisiones de la Unión Europea: *Nasdaq OMX, Chicago Mercantile Exchange, European Energy Exchange* e *Inter Continental Exchange*. De entre todas ellas, *Inter Continental Exchange* (ICE) es la plataforma más activa y concentra la mayoría del volumen.

En el ICE se pueden negociar tres tipos de contratos de futuro cuyo subyacentes son: Derechos de Emisión de la Unión, Derechos de Aviación de la Unión y Certificados de Reducción de Emisiones. Además, es posible negociarlos al contado (futuros diarios) y en los mercados de opciones. No obstante, el contrato de referencia en el mercado es el contrato de futuro con vencimiento anual, el cual vence el último lunes de diciembre.

El mercado de futuros europeos de ICE opera un mercado electrónico dirigido por órdenes con creadores de mercado e intermediarios. La sesión diaria empieza con una pre apertura de 15 minutos (desde las 6:45 hora de Reino Unido) que permite a los miembros del mercado registrar órdenes disponibles para el comienzo de la negociación. La sesión previa a la negociación termina con una subasta, donde el precio de apertura y el volumen son determinados mediante un algoritmo. Durante la sesión continua de 7:00 a 17:00, los inversores pueden enviar órdenes límite, de mercado y órdenes en bloques. El periodo de fijación del precio de cierre va desde las 16:50:00 a las 16:59:59 horas de Reino Unido, el cual, es una media ponderada de las órdenes cruzadas en este periodo. El contrato de futuros es negociado en lotes. Cada lote equivale a 1.000 toneladas de CO_2 equivalentes, esto es, 1.000 derechos de emisión. La unidad mínima de negociación fue 0,05 € hasta el 27 de marzo de 2007 cuando cambio a 0,01 €.

1.4. Datos

El activo sobre el que trata toda esta tesis doctoral es el derecho de emisión de la Unión Europea. En concreto, dado que es la referencia aceptada por el mercado, a lo largo de toda la tesis se ha trabajado con futuros de derechos de emisión con vencimiento diciembre, negociados en ICE, que tal y como se ha indicado anteriormente, es la plataforma que concentra la mayoría de la actividad entre todas las que negocian derechos de emisión.

La base de datos está compuesta por datos diarios e intradiarios. Para ambos, hemos elegido contratos de futuros con vencimientos de 2005 hasta 2020. Las series intradiarias contienen la fecha y la hora de las transacciones, el precio, el tamaño y el signo de la transacción, esto es, tomando información que nos indica si la transacción se ha iniciado por el comprador o por el vendedor. Además, la base de datos de opciones intradiaria que se ha usado contiene el precio de ejercicio. Por otro lado, los datos diarios contienen el precio de apertura, el precio de cierre, el precio máximo, el precio mínimo, el volumen total y el interés abierto. Todos los precios están expresados en euros, la hora está expresada en el huso horario GMT, y el volumen y el interés abierto están expresados en lotes.

A lo largo de la tesis doctoral se han utilizado distintas sub muestras con un doble objetivo: poder obtener la mayor información posible en cada uno de los análisis y comprobar su evolución temporal. En primer lugar, hemos usado ambas series de datos, diarios e intradiarios, para los contratos de futuros del derecho de emisión con vencimiento en 2010. El periodo muestral comprende desde el 21 de septiembre de 2006 hasta el 20 de diciembre de 2010 donde 304.189 transacciones tuvieron lugar. Este contrato de futuro pertenece a la Fase II pero empezó a ser negociado durante la Fase I por lo que podemos comparar si hay alguna diferencia según el periodo en el cual el futuro es negociado.

Posteriormente, se han incluido nuevas series de contratos de futuros para comprobar la evolución temporal de los efectos detectados. En concreto, se han estudiado vencimientos de diciembre de los años 2010, 2011 y 2012. El periodo muestral analizado comprende desde el 21 de septiembre de 2006 al 20 de diciembre de 2010, desde el 23 de marzo de 2006 hasta el 10 de diciembre de 2011 y desde el 23 de marzo de 2006 al 17 de diciembre de 2012 para los contratos de futuros de 2010, 2011 y 2012, respectivamente. De esta forma, se analiza toda la vida de estos tres contratos. Un total de 304.189, 359.003 y 491.205 transacciones tuvieron lugar para el primer, segundo y tercer contrato, respectivamente.

Una vez comprobada la consistencia de los efectos a través de los distintos contratos de futuros, a continuación se construyó la serie continua de futuros con vencimiento en el mes de diciembre. En este caso, todos los contratos eran de la Fase II y el periodo comprende desde el 18 de diciembre de 2007 al 17 de diciembre de 2012. Se utilizaron tres tipos diferentes de datos, diarios e intradiarios para futuros e intradiarios para opciones. La muestra resultante contiene 1.306.765 transacciones para un volumen total negociado de 9.201.096 contratos de futuros y el precio oscilaba entre 5,61€ y 29,69€.

Finalmente, se utilizaron datos diarios e intradiarios de los contratos de futuros con vencimiento en Fase III, más concretamente, se escogieron los contratos de futuros con vencimiento en diciembre de los años 2013, 2014 y 2015. Durante este periodo, desde el 18 de diciembre de 2012 hasta el 14 de diciembre de 2015, se hicieron un total de 1.214.304 transacciones.

2. Objetivos y metodología

El objetivo de esta tesis doctoral es el estudio de determinados aspectos psicológicos que pueden influir sobre el comportamiento de los inversores en el Mercado Europeo de Carbono, poniendo el foco en los precios de los contratos de futuros sobre los derechos de emisión. En concreto, el objetivo es determinar la existencia de agrupación en precios, determinar la existencia de agrupación en tamaños y comprobar su relación con el efecto de la agrupación en precios, analizar la existencia de barreras psicológicas y determinar cómo estas afectan a la dinámica de algunas variables clave tales como son el rendimiento, la volatilidad o el volumen y, por último, investigar la presencia de un efecto gregario entre los inversores en el mercado de derechos.

En primer lugar, se estudia la agrupación en precios, que se define como la tendencia a negociar determinados precios de manera más frecuente que otros, pudiendo afectar esta repetición a la parte decimal del precio, a la parte entera o a ambas. En ausencia de fricciones en el mercado, los precios deberían estar uniformemente distribuidos entre cualquiera de los posibles valores puesto que cada uno de ellos tienen la misma probabilidad teórica de ocurrencia. Por tanto, la aparición de este fenómeno se considera una anomalía en el mercado que ocasiona una ruptura con la Teoría de los Mercados Eficientes.

Por tanto, el primer objetivo de este capítulo es documentar la evidencia de agrupación en precios en el mercado de futuros sobre derechos de emisión cotizados en ICE utilizando datos de transacciones intradiarias. El comportamiento del precio del derecho de emisión es crucial por lo que la investigación de agrupación de los precios del derecho de emisión puede aportar una nueva visión sobre la eficiencia del mercado europeo de futuros de CO_2. Para la elaboración de este estudio, hemos elegido contratos de futuro con vencimiento en diciembre de 2010 pertenecientes a la Fase II del programa.

La primera parte del estudio se centra en observar la distribución del último decimal de la serie de precios y contrastar si sigue una distribución uniforme, lo que supondría el cumplimiento de la Teoría de los Mercados Eficientes. Para determinar el nivel de agrupación del último decimal se ha usado una medida que, aunque suele ser empleada en análisis sobre poder de concentración del mercado, en nuestro caso se ha utilizado para comprobar si los precios están repartidos equitativamente entre todos los valores posibles o, en cambio, comprobar si hay algunos con más peso que otros.

Finalmente, para concluir el estudio sobre la agrupación en precios, se han estudiado los factores clave que provocan este efecto sobre los precios de CO_2 a través de un modelo de análisis multivariante. Basándonos en estudios previos, se han elegido como posibles factores la volatilidad intradiaria, la frecuencia diaria medida como el número de transacciones diarias, el tamaño medio de la transacción y una medida que utiliza el ratio entre la variación diaria del interés abierto y el volumen diario y que se ha utilizado para determinar el nivel de especulación en el mercado.

Posteriormente, tras haber analizado la agrupación en precios, la segunda parte de la tesis se ha centrado en estudiar si los agentes del mercado también agrupan sus órdenes en determinados tamaños y en, tal caso, bajo qué circunstancias ocurre.

Existen numerosos estudios sobre la liquidez de los mercados y, en concreto sobre la liquidez del mercado de CO_2 pero, ningún estudio se ha centrado en estudiar la amplitud de dicha liquidez. Este es un aspecto importante a tener en cuenta ya que la existencia de la agrupación de órdenes en determinados tamaños hace que los inversores no puedan ejecutar sus órdenes a los precios deseados provocando así unos mayores costes de transacción. Por tanto, la capacidad para negociar grandes cantidades a bajos costes puede ser obstaculizada cuando el tamaño de las órdenes se encuentra concentrado en determinados tamaños.

Para la elaboración de este segundo estudio se han utilizado datos de transacciones intradiarias de los futuros sobre derechos de emisión con vencimiento diciembre de los años 2010, 2011 y 2012 cotizados en ICE.

Como paso previo, se ha realizado un análisis de frecuencia de la ocurrencia de los tamaños de órdenes negociados para observar su distribución. Además, se ha realizado una regresión lineal múltiple usando variables ficticias para determinar si los tamaños múltiplo de cinco tienen una presencia significativamente superior al resto. A continuación, para analizar el efecto de la agrupación en tamaños se ha usado una variable que reflejará el número diario de tamaños distintos que se pueden negociar. De este modo, se comprueba si el mercado ofrece un número amplio o reducido de tamaños distintos a los cuales negociar. Utilizando esta variable, se ha realizado una comparación entre las medianas del número de tamaños distintos de le los precios más afectados por el efecto agrupación en precios y la mediana del resto de precios. De este modo, se ha comprobado si hay indicios de que ambos efectos, la agrupación en precios y la agrupación en tamaños son complementarios.

Finalmente, y de nuevo siguiendo la literatura previa, se ha estimado un modelo de regresión lineal multivariante en donde para cada día tendremos dos observaciones, una para la muestra donde los precios están afectados por el efecto agrupación y otra para el resto. De este modo, podremos ver si factores como la volatilidad intradiaria, el número de transacciones diarias, el tamaño medio de la transacción o, el nivel de especulación en el mercado afectan al número de tamaños distintos negociados y si estos tienen un comportamiento distinto en presencia del efecto agrupación en precios o no.

Una vez concluido el estudio sobre la agrupación en tamaños y precios nos interesa saber si determinados precios, a los cuales los participantes del mercado le atribuyen propiedades diferenciadoras, alteran el normal funcionamiento de los mercados, influyendo en factores clave tales como el rendimiento, la volatilidad o el volumen negociado de los derechos de emisión.

El estudio del comportamiento pasado de los precios y otros indicadores como el volumen negociado es ampliamente usado en el análisis técnico, el cual es frecuentemente aplicado tanto por la comunidad inversora como por un amplio número de medios de comunicación financieros. En concreto, los medios tienden a utilizar expresiones tales como precios barrera, soportes o resistencias para referirse a determinados niveles de precios que aparentemente parecen influir en el comportamiento de los inversores. Durante este estudio, se ha analizado la presencia de precios barrera en el Mercado Europeo de Carbono. Conviene señalar que este mercado está dominado por profesionales por lo que las influencias psicológicas deberían jugar un rol limitado.

Para analizar la existencia e impacto de determinados precios clave en el mercado de emisiones hemos utilizado la serie continua formada por los vencimientos en diciembre para la Fase II del mercado (los futuros con vencimiento diciembre 2008, 2009, 2010, 2011 y 2012).

A lo largo de este tercer estudio nos hemos centrado en la búsqueda de los llamados precios barrera que forman resistencias o soportes, los cuales son precios identificados por los agentes de mercado como de especial relevancia y donde sistemáticamente la cotización no puede exceder de este precio en una tendencia alcista o rebasarlo a la baja en una tendencia bajista. Se ha analizado la existencia de estas barreras a diferentes niveles del precio, donde cada nivel es una representación numérica de dos dígitos del precio. En nuestro caso, se ha estudiado el nivel 0, compuesto por los dos decimales del precio, y el nivel 1, compuesto por la unidad y el primer decimal. Para su análisis, se ha comprobado las distribuciones del precio en ambos niveles, a las que se ha aplicado un test de bondad con el fin de comprobar si la distribución empírica se ajusta a la distribución esperada, o si por el contrario, hay unos precios más frecuentes que otros. Esto es importante ya que en nuestro caso son susceptible de ser barrera aquellos precios con una frecuencia mayor. Alrededor de estos precios identificados como potenciales precios barrera, se ha definido dos bandas, una superior y otra inferior, a las cuales les hemos dado el mismo tratamiento de precio barrera ya que la cotización podría empezar a verse influenciada por la cercanía a estos precios clave, sin llegar a tocarlos

Un precio se ha considerado como barrera si, cuando la cotización alcanza dicho valor, éste afecta significativamente al comportamiento del mercado. Para comprobar este hecho, se han definido cuatro variables ficticias cada una de las cuales toma valor 1 tres días antes de tocar la barrera en un movimiento alcista y los tres días posteriores a tocar la barrera en un movimiento alcista, tres días antes de tocar la barrera en un movimiento bajista y los tres posteriores a tocar la barrera del movimiento bajista. Estos cuatro escenarios se han incluido en la estimación de un modelo ARMA-GARCH, más concretamente un EGARCH(1,1). El objetivo es comprobar cómo se comportan el rendimiento y la volatilidad en estas cuatro situaciones. Por último, y siguiendo la misma metodología que en el estudio del resto de sesgos psicológicos, se ha analizado el comportamiento de otras variables como el volumen o el interés abierto mediante un modelo de regresión lineal.

La última parte de la tesis doctoral se ha centrado en el conocido efecto gregario o efecto rebaño. En un sentido general, el comportamiento gregario puede ser definido como el acto de poner juntos a los animales en un grupo con la intención de guiarlos de un lugar a otro. Aunque este comportamiento es comúnmente usado para describir el comportamiento de los animales, también podemos encontrar este comportamiento en humanos afectando al proceso de toma de decisiones en campos como las finanzas. El comportamiento gregario en finanzas es interpretado como la tendencia de los inversores a imitar las acciones de otros inversores, dicho efecto imitación puede suponer que unos inversores cambien su propia opinión para adoptar el criterio que sigue la mayoría. En la práctica, alguien en el mercado que tenga conocimiento acerca de la existencia del efecto rebaño y empezase a observar señales tempranas de que se está formando un proceso de imitación, podría poner órdenes para tomar ventaja de este efecto con la expectativa de que la tendencia va a continuar y con la intención de cerrar sus posiciones antes de que dicho efecto desaparezca.

El cuarto capítulo analiza la presencia del efecto imitación en el mercado europeo de emisiones, caracterizado por ser un mercado ciego en donde la gran mayoría de los participantes en el mercado son institucionales. Por tanto ambas características nos permiten, estudiar la existencia del efecto rebaño bajo condiciones muy restrictivas. Para el análisis se han elegido futuros con vencimiento diciembre de la Fase III, concretamente los correspondientes a los años 2013, 2014 y 2015, negociados en ICE.

Una forma intuitiva de estudiar la presencia del efecto gregario es analizar la evolución en el cambio del signo de los precios del derecho de emisión, observando series crecientes o decrecientes en los cambios del precio en el caso de estar presente este efecto imitación. Además, debido al efecto barrera descrito anteriormente también admitiremos como parte de un proceso de imitación no solo aquellas sucesiones de precios que sean estrictamente alcistas o bajistas sino también aquellas en las que el precio se repite. Para comprobar si las secuencias formadas por los cambios del signo del precio se producen de forma aleatoria, o por el contrario estas rachas son fruto de un efecto imitación, se ha aplicado un test de rachas.

Una vez identificada la existencia de este fenómeno, el siguiente objetivo ha sido medir la intensidad del efecto gregario y estudiar su impacto, tanto en la dinámica del precio del derecho de emisión como en las variables más importantes del mercado. A tal fin, se ha elegido una medida que refleja la intensidad del efecto imitación que nos permita capturar las secuencias intradiarias además de analizar la evolución diaria del futuro bajo cualquier circunstancia y no solo en circunstancias de rendimientos extremos como ocurre con otras medidas usadas en la literatura. Este estudio sobre las dinámicas del precio del CO_2 se ha llevado a cabo a través de una regresión lineal, donde se ha comprobado si a medida que el mercado es más maduro el efecto persiste, y donde se ha analizado si en el periodo de más especulación el nivel del efecto rebaño varía. Adicionalmente, se ha incluido una variable que identifica el nivel de agrupación en precios, analizado al principio de la tesis doctoral, y, por último, una variable ficticia que tomará valor 1 los días en los que la Comisión Europea ha revelado información importante para el mercado y 0 el resto de días.

Tras estudiar los factores clave que afectan al comportamiento imitación en el mercado de derechos, se ha analizado el comportamiento de las variables de mercado ante el efecto imitación. Este análisis consistirá en una regresión lineal sobre el residuo de la estimación anterior. En concreto, las variables independientes que se incorporarán han sido el número de transacciones diarias, la volatilidad intradiaria, el tiempo hasta vencimiento de cada contrato y dos variables ficticias que capturan rendimientos extremadamente altos y bajos.

Para finalizar, se ha estudiado si el efecto imitación puede llegar a desestabilizar el mercado alterando el comportamiento de los rendimientos y/o de la volatilidad, para ello se han regresado contra estos dos factores la variable que mide la intensidad del efecto gregario hasta con 5 retardos. De esta forma se ha estudiado si el efecto rebaño influye en las decisiones posteriores que toman los agentes del mercado.

3. Resultados

En primer lugar, los resultados sobre la agrupación en precios muestran que existe una fuerte repetición del último decimal en ciertos valores, principalmente en 0 y 5, los cuales presentan una frecuencia de ocurrencia estadísticamente más elevada que el resto de decimales. Este hecho es además, corroborado por las medidas de concentración de mercado analizadas. También se observa que pese a que este efecto es persistente a lo largo de toda la muestra, hay una ligera reducción de su importancia con el paso del tiempo, hecho que podría venir explicado por la *hipótesis de atracción.* Aplicando la misma metodología a distintos escenarios como precio el máximo, el precio mínimo, el primer precio del día, el último negociado y el precio de cierre observamos que todos los casos presentan este efecto de agrupación en precios salvo el precio de cierre, que presenta una distribución uniforme.

El análisis multivariante indica que la agrupación de precios se incrementa cuanto mayor es la volatilidad del mercado y disminuye cuanto mayor es la liquidez del mismo, es decir, cuanto menor es la información disponible en el mercado. Estos resultados sugieren que la concentración de los precios en determinados números es debido a que los participantes del mercado intentan hacer menos costosas sus operaciones. Por tanto, además, de la *hipótesis de atracción* parece tener cabida también como explicación de este sesgo psicológico la *hipótesis de negociación*.

Los análisis posteriores sobre la agrupación en tamaños revelan que la concentración de precios sigue vigente para contratos posteriores al vencimiento del 2010. Los primeros resultados acerca de la agrupación en tamaños muestran que la mayoría de los tamaños negociados son de pequeña magnitud, hecho que podría explicarse por la preferencia de los inversores a la hora de negociar tamaños de órdenes pequeños con el fin de no revelar información al resto del mercado. Además, la regresión lineal efectuada sobre los tamaños en múltiplos de 5 muestra también que estos tamaños tienen una presencia mayor que el resto de tamaños.

El análisis multivariante realizado con el fin de conocer los factores clave que afectan a la agrupación en tamaños arroja varios resultados interesantes. En primer lugar, se observa que el efecto redondeo tiene lugar al mismo tiempo en tamaños y en precios. En segundo lugar, el modelo de regresión múltiple muestra que la volatilidad es mayor en presencia del efecto redondeo en precios y, en tercer lugar, se observa que la concentración de los tamaños se incrementa en aquellos días donde la liquidez del mercado es menor y en los días donde hay aperturas o cierres masivos de posiciones en contratos de futuros.

Respecto al estudio llevado a cabo sobre las barreras psicológicas, los primeros resultados muestran la existencia de determinados precios clave que afectan de forma significativa a la evolución de la cotización del mercado de derechos de emisión. Encontramos, en primer lugar, que tanto para el caso de los números decimales (nivel 0) como para las unidades y el primer decimal (nivel 1) hay determinados valores cuya distribución empírica distan de su distribución teórica y, por tanto, son susceptibles de ser precios barrera.

La estimación del modelo EGARCH(1,1) realizada para comprobar el efecto de estos precios barrera sobre los rendimientos y sobre la volatilidad en los diferentes escenarios analizados muestra que el precio al llegar a estas barreras o bien toca la barrera e invierte la tendencia actual o se mantiene alrededor de la barrera. En el análisis de la volatilidad, se observa que ésta es mayor antes de alcanzar los precios clave y se reduce una vez que se han superados. Por último, con respecto al volumen, se observa que este decrece en movimientos alcistas donde el precio se aproxima a la barrera.

Los resultados de la existencia del efecto imitación en el mercado de derechos de emisión muestran cierto efecto gregario debido a la ausencia de aleatoriedad en las secuencias de cambios positivos o negativos en el precio del derecho. A este respecto, habría que añadir que la presencia de precios psicológicos hace que la longitud de las secuencias se incremente, sin necesidad de que estas sean estrictamente alcistas o bajistas.

Un análisis de las pautas del mercado de derechos de emisión muestra que el efecto rebaño se intensifica con el nivel de especulación y otros sesgos psicológicos tales como la agrupación en precios. Al mismo tiempo, también se observa que cuando la Comisión Europea publica información relevante sobre el mercado, la intensidad del efecto rebaño se intensifica, influyendo especialmente a aquellos inversores que posicionan órdenes de venta.

En el estudio de la relación del efecto gregario con las principales variables del mercado detectamos mayor efecto imitación cuando la incertidumbre aumenta y cuanto mayor es el número de transacciones. Finalmente, mostramos que este efecto imitación contribuye a la desestabilización del mercado, dado que tanto la volatilidad como los rendimientos se ven alterados por el grado de imitación de días anteriores, lo que provoca que los participantes del mercado acaben sobrerreaccionando.

4. Conclusiones

Esta tesis doctoral analiza la influencia de cuatro aspectos del comportamiento de los agentes negociadores en el mercado de derechos de emisión de la Unión Europea. A continuación se expondrán las principales conclusiones obtenidas.

Hemos demostrado la existencia de agrupación en precios, donde las terminaciones de los precios tienden a estar concentradas en precios terminados en 0 y 5. Esta concentración de los precios es mayor cuando mayor es la ausencia de información en el mercado, mayor es la volatilidad y menor es la frecuencia de negociación

En primer lugar, el conocimiento de este fenómeno es importante, primero porque esta medida podría ser empleada para reflejar la cantidad de información disponible en el mercado. En segundo lugar, dado que los precios no siguen un camino aleatorio los gestores de riesgos deberían dedicar un mayor esfuerzo a la hora de encontrar modelos alternativos que tengan en cuenta el agrupamiento de precios. En tercer lugar, el conocimiento de este fenómeno puede derivar en estrategias ganadoras en el Mercado Europeo de Carbono.

Se ha demostrado la existencia del efecto de agrupación de los tamaños de las órdenes, donde los inversores tienden a agrupar sus órdenes en tamaños pequeños o en números múltiplos de 5 contratos con el fin de simplificar el proceso de negociación. Nuestros análisis también detectan que la agrupación en precios y tamaños en el Mercado Europeo de Carbono son fenómenos complementarios por lo que los participantes en este mercado fijan órdenes redondeando tanto precio como tamaño de la transacción. Además, observamos que este fenómeno se ve intensificado cuando la volatilidad es alta, hay poca liquidez y cuando el deseo de abrir o cerrar posiciones es alto.

El resultado del estudio demuestra la imposibilidad de los participantes del mercado de derechos a la hora de negociar los tamaños de órdenes que deseen. Esto implica que los agentes que deseen negociar grandes cantidades deberán hacerlo en precios que terminen en múltiplos de 0 o 5 y, a la vez, reducir el tamaño de las órdenes o partir las órdenes en múltiplos de 5.

Hemos mostrado también la existencia de precios clave que modifican el comportamiento de los actores del mercado. Este fenómeno puede ser explicado tanto por la existencia de agrupación en precios como por el redondeo en los precios de ejercicio de opciones sobre el derecho de emisión.

Cabría añadir también que la presencia de precios clave afecta a la volatilidad, incrementándola antes de tocar la barrera y disminuyéndola después de tocarla. Este efecto barrera del precio afecta también a las dinámicas del rendimiento, haciendo que se revierta o se estanque al llegar al precio barrera, y del volumen, el cual disminuye al aproximarse la cotización al precio clave.

Finalmente, en esta tesis doctoral mostramos por primera vez la existencia del efecto imitación en el mercado de derechos de emisión, a pesar de ser un mercado ciego. Además, este efecto se incrementa cuando la cotización del derecho se acerca a los llamados precios barrera y ante la presencia de sesgos psicológicos como la agrupación en precios. Por último, también encontramos que el efecto gregario se intensifica con el aumento de la incertidumbre y en los días con rendimientos extraordinarios, mientras que por el contrario, este efecto se reduce cuando el contrato se acerca a su vencimiento.

El estudio sobre el efecto gregario puede ser de interés tanto a académicos como para los participantes del mercado. Por un lado, añade una nueva visión a los escasos estudios sobre este fenómeno en mercados de futuros y, por otra parte, el efecto gregario puede implementarse en el desarrollo de estrategias de negociación en mercados de futuros sobre el CO_2 a pesar de ser un mercado ciego.

5. Líneas de investigación futuras

Esta tesis doctoral ha estudiado la influencia de las finanzas del comportamiento sobre el Mercado Europeo de Derechos de Emisión sobre el CO_2. De hecho, este trabajo podría ser considerado como un punto de partida en el estudio de como el comportamiento humano influye en el mercado de derechos.

Como se ha dicho anteriormente, el estudio desarrollado acerca de los precios barrera, es el primero en analizar el papel que juega el análisis técnico en el mercado de derechos. Este trabajo puede ser extendido con el estudio de otras herramientas de análisis técnico tales como el uso de medias móviles o las bandas de *Bollinger*. Además, sería de interés para este tipo de análisis desarrollar un método que permita determinar el horizonte temporal en el cual un precio psicológico tiene efectividad y evaluar todos estos estudios a un nivel intradiario.

Otra línea de investigación se puede desarrollar a partir del estudio sobre el efecto imitación. En concreto, se puede extender este análisis desde dos enfoques. El primero estaría relacionado con el estudio del efecto gregario en tamaños en lugar de en órdenes, puesto que análisis preliminares realizados en el cuarto capítulo mostraban que la primera orden de la secuencia tiene un tamaño estadísticamente superior al resto. Además, el estudio sobre el nivel de autocorrelación en el volumen podría ofrecer nuevas conclusiones para desarrollar estrategias de inversión ganadoras que permitieran tomar mejores posiciones en términos de tiempo y precio. El segundo enfoque del efecto gregario estaría basado en el estudio de este fenómeno entre proveedores de datos y cámaras de negociación ya que sería de interés conocer si los principales proveedores de datos y plazas de negociación hacen publica las transacciones al mismo tiempo y si el precio es igual o, al contrario, si existe un líder que es el primero en ofrecer nuevos cambios en la cotización y los otros le siguen. Esta información es muy importante a la hora de elegir.

Adicionalmente, una futura línea de investigación futura que podría ser aplicada a todos los capítulos es el estudio del poder predictivo de las anomalías detectadas analizando la rentabilidad de de varias estrategias de negociación con datos fuera de muestra. Para tal fin, sería necesario establecer las reglas que definen cuando entrar en el mercado de emisiones y cuando salir de él.

Alternativamente, una de las propuestas que la Comisión Europea está estudiando de cara a reformar el Esquema Europeo de Emisiones es el establecimiento de un túnel en el precio del derecho de emisión. Los defensores de esta idea argumentan que esta medida dará más estabilidad al mercado, ya que aquellos que inviertan en tecnologías bajas en emisiones verán reducido el riesgo de costear dichas mejoras mientras otros competidores que no hayan invertido en dichas tecnologías se estarían beneficiando de unos precios del derecho de emisión bajos. La inclusión de un precio suelo animaría también a muchas industrias sujetas al programa a poner en marcha inversiones bajas en emisiones.

El precio suelo estaría controlado a través de las subastas, si el precio de la subasta cayera por debajo del umbral inferior, la subasta sería cancelada y los derechos pasarían a la reserva hasta que el precio alcanzara el umbral superior. Además, este precio mínimo del derecho de emisión iría evolucionando anualmente siguiendo un patrón determinado.

Pues bien, la inclusión de esta nueva medida podría motivar nuevos estudios acerca del comportamiento de los participantes del Mercado Europeo de Carbono, como por ejemplo, el uso de opciones con precio de ejercicio en el precio suelo los días de subasta. Por otro lado, podríamos interpretar este canal como nuevas barreras psicológicas, por lo que se podría analizar el comportamiento de los inversores cuando el precio está cerca de este umbral superior o inferior.