Essays in Global Commodity Prices and Realised Volatility

Essex Business School

University of Essex

Qualification sought: PhD in Finance

By

Abril Imelda Rosen Esquivel

Date of submission for examination: September 2019

Thanks and Acknowledgments

I thank God, my parents Imelda and Patricio, and the ESRC through the University of Essex for the giving me the financial support during the first three years, without which I could not have finished my PhD and also the CONACYT from Mexico for the financial support during the fourth year. Specially I would like to thank both my supervisors Professor Neil Kellard and Professor Simon Price for their great work and support throughout the course of my PhD at the Essex Business School and Professor Jerry Coakley for his essential support and for being the chair during my journey. I thank my brothers, Karol, Omar and Patricio; and my friend John Wayne for helping me revising the use of English, finally I apologise for not naming all the people who have been crucial in obtaining my PhD.

Abril Rosen September 2019

Abstract

This thesis consists of three substantive chapters and an Introduction and a Conclusion. The first substantive chapter (Chapter 1) examines in whether high frequency financial and speculative variables convey information that improves the monthly predictions of an aggregate measure of commodity prices (S&PGSCI) by comparing their Root Mean Squared Error (RMSE) to that from the usual benchmark AR (1). The Mixed Data Sampling models (MIDAS) allow us to obtain forecasts by keeping variables at their original frequencies and therefore to explore the richness of high frequency data. The evidence suggests that MIDAS models estimated recursively, and their analogous monthly version seem to capture some predictive information contained in the speculative variables described by the agricultural managed money spread positions. The most interesting finding – larger RMSE reductions during the crisis period - is an improvement in prediction accuracy from use of speculative positions. This suggests speculation contains information that helps in forecasting commodity prices.

The second substantive chapter (Chapter 2) focuses on the ability to forecast the daily Realised Volatility of the Bloomberg Commodity Index Excess return (BCOM) using an Heterogeneous Autoregressive model (HAR) and competing models that include an Implied Volatility (IV) measure either from the Commodity or US Stock Market. The former uses the IV for at the money call options of the Dow Jones-UBS Commodity Index published by DataStream while the latter uses the US Stock Market VIX. The Realised Volatility is measured by three different proxies, absolute returns and two range-based estimators, one based on Parkinson (1980) and the Rogers and the other on Satchell (1991). Both are constructed with open, close, high and low daily prices. In-sample results for the 28/07/2011 to 31/10/17 period show that the IV measure estimates are small but statistically significant, suggesting the IV is a biased estimator of future Realised Volatility. The models used to obtain the one-day-ahead out of sample forecasts from 03/03/16 to 31/10/17 were estimated dynamically following a rolling window. To compare the forecasting accuracy of the models, their respective Root Mean Squared Error (RMSE) were computed. These show that the HAR specification does a good job in forecasting the Realised Volatility

by offering better forecast in comparison with the IV measures and popular benchmark models such as GARCH (1,1), E-GARCH (1,1).

The third substantive (Chapter 3) investigates the linear Granger causal relationship between a popular speculative proxy of 'excess speculation' (Working’sT index) and the weekly log realised volatility and log returns of wheat futures prices. It also examines the impact of managed money spreading positions as a novel measure of speculation on wheat futures causality. Following Granger and Vector Autoregressive (VAR) methodology, I estimate bivariate VAR regressions. The findings show there is a statistically significant unidirectional linear causality between speculative measures and both wheat log returns and the log realised volatility proxy - the Rogers and Satchell’s range-price estimators. Interestingly, the direction of causality runs from managed money spreading positions to log volatility and log returns but in the opposite direction for the Working’s T index.

Table of Contents

Introduction

Commodity prices are of significant importance to the economy because they constitute a forward-looking measure of general price expectations and are linked to the world economic and financial activities. Hence the relevance of obtaining good commodity prices forecasts, not only for policy makers such as central banks - with regard to inflation - but also for investors and fund managers, the latter investing in commodities to benefit from risk diversification with respect to asset portfolios. (Gargano and Timmerman, 2014). Likewise, improving the forecast performance of the volatility of commodity returns is also essential since it may provide significant information on price determination. That is one of the main reasons why the financial literature has tried to find ways to improve the forecasts of diverse measures of volatility: latent conditional volatility and realised volatility which ultimately can be of use in portfolio allocation (see Andersen, Bollerslev, Diebold, and Labys, 2003).

Understanding commodity dynamics requires the role of fundamentals, supply and demand factors (for instance Kilian, 2014), but also the role of speculation. The financial literature does not exhibit a consensus about which especially has had a bigger effect overall on financial assets including commodities after the financial crisis of 2008. With respect to speculation, some authors have found evidence which shows that some speculative measures such as open interest (Hong and Yogo, 2012), and index-investing and managed money spreading positions have been important driving forces of commodity price dynamics. This is because these measures carry information relevant to the time varying risk premiums in a context of heterogeneous beliefs, in particular, during periods of economic and financial uncertainty (Singleton, 2014).

Consequently, I conduct two empirical exercises in seeking to contribute to the forecasting literature of global commodity price returns and realised volatility. The results are discussed in the first two substantive chapters of the thesis. Specifically, Chapter one aims to fill the gap in the forecasting literature of commodity prices in various manners, first by obtaining the 1-step ahead forecast of monthly global commodity returns of the S&P GSCI spot index (Goldman Sachs Commodity Index), in a mixed frequency data context, in the Mixed Data Sampling models (MIDAS) framework. In order to try to exploit high frequency data of daily financial variables and commodity currencies which have been proven to carry predictive power on forecasting commodity returns, but also with the novelty to find if a measure of speculation understood as managed money spreading positions is useful to improve the forecasts of commodity returns relative to a usual benchmark AR(1). Previous studies regarding commodity prices in a MIDAS framework have only conducted empirical exercises on the crude oil and corn spot markets, as the studies of Baumeister, Guérin, and Kilian (2014) and Etienne (2015).

In particular financial variables were currencies, interest rates and the Baltic Dry Index, and speculative data were agricultural managed money spreading positions at the daily and weekly frequencies, respectively. Out- of-sample one-step ahead forecasts are estimated for the period 2000-2016 and some subperiods depending on data availability, both recursively and by the rolling window method with the Mixed Data Sampling models (MIDAS) and a monthly version estimated for the speculative positions. The Root Mean Squared Error (RMSE) of these forecasts are compared with the RMSE of the forecasts obtained from the usual benchmark Autoregressive model AR (1). The most interesting finding is that by including agricultural speculative positions in the forecasting equation, these forecasts can be better than the benchmark forecasts, particularly during the crisis period regardless of the model. Likewise results indicate that regarding currencies MIDAS models estimated recursively offer lower RMSE relative to the rolling window version.

The research in Chapter two aims to add to the forecasting literature on the volatility of commodity prices, and in particular to forecast proxies of daily realised volatility of global commodity prices. Most of the previous research regarding forecasting realised volatilities has focused on forecasting the realised volatility of stock markets, measured by the 30 min returns and the realised kernel such as Hansen and Lunde (2011). And regarding a general measure of commodities such as the S&PGSCI, studies have centred their attention on the impact of news on the volatility of such commodity index (see Smales, 2017) or forecasting monthly volatility from log returns under a Bayesian approach within the context of variable selection. (Christiansen, Schmeling and Schrimpt, 2012). In this regard, the contribution of my second Chapter is to forecast de 1-step ahead forecast of the three proxies of daily realised volatility of global benchmark of commodities the Bloomberg Commodity Index Excess return (BCOM) in a HAR framework to capture the persistence of the volatility, and compared these forecasts with the forecasts of conventional models such as GARCH(1,1) and EGARCH(1,1) while also studying if measures of implied volatility of commodities and stock market improve the forecast of the HAR specification.

With respect to ex-ante studies of implied volatility there is not a lot said about implied volatility and a global measure of commodity prices, for example, Viteva, Veld-Merkoulova, and Campbell (2014) analysed the forecasting accuracy of implied volatility on three measures of realised volatility: squared returns and two range-price estimators for the Carbon Market.

Consequently, the interest of the empirical exercise of my second Chapter is to forecast the daily realised volatility (RV) of the Bloomberg Commodity Index Excess return (BCOM) for the period March 2016 to October 2017. The use of high-frequency data has proven to be helpful in forecasting the highly predictable realised volatility process (see for example Hansen, and Lunde, 2011). It follows that the use of two range-price estimators (Parkinson (1980) and Rogers and Satchell (1991)) computed with intra-daily data make sense as realised volatility measures along with the absolute returns. Furthermore, one of the novelties of this study is precisely the use of the two range-based estimators as realised volatilities proxies.

Thus, the one-day ahead forecasts were estimated using the Heterogeneous Autoregressive model (HAR) and competing models which were all computed dynamically following a rolling window, and which also incorporate an Implied Volatility measure (IV) either from the US stock market (VIX) or the Commodity market itself. Thus, RMSE metrics were obtained in order to compare the forecasting accuracy of the competing models. The forecasts obtained with HAR specifications were also compared to those from the popular GARCH (1,1) and E-GARCH (1,1) models, which have proven difficult to beat (see for instance Bentes, 2015). The main findings of the second essay provide evidence that suggests the HAR specification does a good job in forecasting the RV by providing forecasts which outperform competing models that include IV measures and the above GARCH specifications.

Given the heated debate in the financial literature surrounding the role of speculation in explaining commodity price dynamics along with the findings of Chapter one, where managed money spreading positions help to improve the forecasting accuracy of monthly global commodity returns, the natural question that follows is to try to understand speculation as a driver of commodity returns and a realised volatility measure (range-price estimator). Thus, Chapter three focuses on exploring the possible linear causality which may exist between weekly commodity log returns and log realised volatility of Chicago Board of Trade Wheat, and two alternative speculative measures: Working's T- Index – as a measure of "excess speculation" relative to hedging- and the weekly log change of managed money spreading positions.

One of the original features of this empirical exercise is precisely the use of managed money spreading positions as a speculative proxy in the context of linear causality. The methodological approach is to estimate bivariate Vector Autoregressive models (VAR) for a period which spans January 2008 to June 2018, for each of the two speculative proxies on the weekly log realised volatility and log returns. The empirical evidence suggests that the speculative measure actually matters in relation to the direction of the causal relationship. If speculation is defined as the popular "excess speculation", results are in line with main findings of the literature (see Andreasson et.at.al., 2016). However, when using the alternative speculative proxy, the findings exhibit statistically significant unidirectional linear causality from the log change in managed money to both log returns and log realised volatility proxy. For instance, this last result support the hypothesis that speculation had an impact on the food crisis during the financial turmoil of 2008-2009.

Most of the previous research has studied linear Granger causality of returns in commodity markets focusing on the causal relationships in the crude oil markets, and the link between crude oil markets and exchange rates or agricultural markets such as Nazliogu and Soytas. Regarding causality between commodity futures returns and a measure of excess speculation Working's T Index is the study of Buyuksahin and Harris (as cited in Andreasson et. al, 2016) and the more comprehensive study about the impact of excess speculation and other factors such as exchange rates and implied volatility of the US stock market on diverse commodity futures returns. Hence another originality of my third chapter is to study the linear causality of speculative measures not only on wheat commodity returns but also on a proxy of a realised measure of volatility.

Finally, each of the three Chapters is organized in five sections as follows: The first section is devoted to depicting the existent literature which is of importance regarding the topic of interest with the corresponding subsections. The second, describes the data used to estimate the models and the respective forecasts or causal analysis accordingly. The third section describes the methodological framework, the section reports the main findings and portrays the empirical analysis, and the final section draws conclusions.

The conclusions section takes an overview of the main findings of the three chapters and points to areas for future research.

Chapter 1

1. Commodity price forecasting using a Midas framework and the role of managed money positions

1.1 Introduction

As commodity prices are linked to world economic and financial activity, and constitute a forward-looking measure of general price expectations, economic agents need to know how to obtain good forecasts of these prices (Gargano and Timmerman 2014). Hence, natural questions are whether high frequency financial variables, including commodity currencies and managed money spreading positions (financialization of commodities) could offer over the monthly horizon more accurate commodity price forecasts or not relative to the benchmark AR(1), and how to exploit this potentially rich information set of high frequency financial series which are accurate and available without significant delay.

Given the endogenous nature of commodity prices, many studies such as Kilian (2013) and (2014) and Hamilton and Wu (2013) have shown that supply and demand fundamentals have been crucial in determining the behaviour of commodity prices. However, others such as Singleton (2014) suggests that supply and demand dynamics fail to explain the variation in prices during high financial uncertainty periods, such as the one experienced throughout the financial crisis of 2008-2009.

Some studies have found that open interest is useful in predicting returns, for example Hong and Yogo (2012). Based on their findings Singleton (2014) argues that the index-investing and managed money spread positions are relevant to explain oil futures prices fluctuations through risk premiums in a context where heterogeneous beliefs allow for time-varying risks. Therefore, during crisis episodes, the financialization of commodity markets has been an important driving force of commodity prices. Finally, literature has also documented the relevance of monetary policy in explaining commodity prices behaviour, where interest rates hold a negative relationship with these prices (Frankel, 2006 and Varadi, 2013).

Hence, in order to assess the forecasting accuracy of financial and speculative variables in forecasting the monthly return of commodity prices, the researcher needs to deal with models that incorporate proven useful predictors into their model estimations in a mixed frequency data context. Some plausible methods to tackle this mixed frequency data issue are either to follow the common approach of matching the frequency of the independent and dependent variables by using weighted averages, or to incorporate mixed frequency data in a special fashion model. However, the most popular method of equally weighted averaging the higher frequency data may lead to models which suffer from an omitted variable specification problem, where a parsimonious parameterized weighted average function, in a Mixed Data Sampling (MIDAS) framework, is estimated to deal with the potential inefficiencies and biases caused by the omitted variable (see Ghysels, 2015).

Recent literature has shown the benefits of combining high frequency variables to forecast lower frequency data, in particular when forecasting quarterly variables (GDP) into monthly variables, and monthly series (Volatility) into daily series, (for example Marsilli (2016) and Ghysels, Synko, and Valkanov 2007). However, for commodity prices, interest has been focused on the crude oil and corn markets as in Baumeister, Guérin, and Kilian (2014) and Etienne (2015).

Empirical evidence in forecasting commodity prices with mixed frequency has shown no real gains when using univariate MIDAS models to forecast the crude oil and corn prices. In particular, Baumeister, Guérin, and Kilian (2014) have documented for horizons from 1 to 24 that incorporating high frequency financial data to the monthly forecast of the real price of crude oil do not consistently offer better forecasts than common benchmarks. The results in Etienne (2015) are in line with these findings for forecasting the monthly corn US prices for the immediate future by using financial data.

However, the literature has not examined speculative positions as potential predictors to forecast and aggregate measure of commodity prices in a mixed frequency data context. Available studies are for oil and corn markets by using high frequency financial and macroeconomic data. Thus, encouraged by the previous research, one of the objectives of the current exercise is to try to explore if the information embodied in high frequency financial, commodity currencies and speculative positions data helps to forecast the monthly return of a global measure of commodity prices (S&PGSCI). By the use of MIDAS models the estimations can be done in a parsimonious fashion.

The aim of this research is therefore to determine whether there is any improvement in forecasting accuracy of predicting monthly commodity prices returns by means of high frequency financial and speculative predictors in a MIDAS framework, relative to the AR(1) process. The set of high frequency relevant predictors is based on previous findings. Then, following this Mixed Data Sampling methodology I generate the one step ahead out of sample forecasts of the S&PGSCI return[1] (benchmark of commodity price performance and global prices) and their respective Root Mean Squared Error (RMSE) as a measure of forecasting accuracy.

The chapter is organized in five sections. The first section describes previous findings in the literature regarding commodity prices forecasting, subdivided into three parts which discuss the role of fundamentals (supply and demand) and the role of speculation on explaining commodity prices, and the last part of the literature review provides with findings regarding commodity oil futures prices and corn spot prices forecasting in a Mixed Data Sampling context. The second section describes the data that is used to estimate the univariate MIDAS models. The set of predictors contains financial variables -the Baltic Dry Index (BDI), and the 3-Month Treasury bill-, five commodity currencies in US terms- Canadian, Australian and New Zealand dollar, South African Rand and Chilean peso-, and speculative positions measured

[1] For my computations, I use the end-of-month official closing prices denominated in US dollars of the S&PGSCI Commodity Spot Index.

by the managed money spreading positions of futures agricultural markets: corn, wheat and soybeans and my own measure of grains.

Methodology is explained in Section three which in the first part describes MIDAS model specifications with estimated weights and unrestricted U-Midas models. The estimated weights are data driven and computed from an exponential almon and beta polynomial lag specifications which require non-linear methods. On the unrestricted case the parameters are estimated linearly. The methodological section also describes the MIDAS forecasting equation and the monthly model specification, along with the equations that allow to generate forecasting combinations.

Section four is the empirical analysis which is subdivided into two subsections. The first aims to assess any improvement on commodity forecasting by means of financial variables and commodity currencies relative to the AR(1) process and also includes a forecasting combination exercise. The second subsection examines the predictive power of speculative positions on commodity prices by using not only MIDAS models but also monthly specifications and comparing with the AR (1) benchmark and previous findings in the literature. The final section presents the main conclusions.

1.2 Literature Review

1.2.1 The role of supply and demand on explaining spot commodity prices

Given the link among commodity prices, world economic activity and general price levels, diverse research in forecasting and explaining the changes in commodity prices has been conducted (see Gargano and Timmerman, 2014). The modern literature is composed of two major branches: fundamentals[2] and speculation

[2] For example, Kilian (2013) argues that to understand the dynamics of the price of oil there is need to know the interaction among the oil price and macroeconomic aggregates by using structural models, which explain the dynamics of the price of oil and macroeconomic variables. Kilian´s

(financialization of commodities)[3] as the drivers of commodity prices. Relevant contributions for the oil spot and futures markets include Kilian (2013), Hamilton and Wu (2013) and Singleton (2014). These authors, except Singleton, support the fundamentalist view to describe commodity price performance, since their empirical evidence is negative relative to the role of financialization.

One of the fundamentalist supporting evidence is offered by Kilian (2013) whose study examines the causes of the crude oil prices dynamics in the US markets, which is more complex than previously thought. Traditionally it has been said that exogenous oil supply disruptions in the Middle East were the drivers of oil price increments, but lately it has been accepted that the price of oil is determined endogenously and depends on the performance of the economic growth, due to this reason it is necessary to use structural models to disentangle the causal relationship between the oil prices and the economy, without disregarding the evolution of oil markets.

Kilian argues that shifts in aggregated demand were the principal cause of oil price increases not only for 1973-1974, but for all the subsequent periods, explaining more than 70% of the price variations rather than supply shocks. Flow demand refers to the demand for oil to be consumed in refined products, which is the result of an expanded global economy.

The role of expectations in the physical oil market is considered the role of speculative demand shocks, because what activates speculative demand is the expectation of higher oil prices due to more economic growth or due to a supply disruption relative to demand. Kilian (2013) states that for the past periods: 1979,

---

evidence shows that the increase in oil prices was mainly due to a shift in aggregated demand as an endogenous response to economic growth from the emerging markets.

[3] For instance, a relevant document analysing the role of speculation in oil futures commodity markets is the one of Singleton (2014). Speculation is described by examining the source of variation of oil futures risk premia. Given limits to arbitrage, heterogeneous beliefs among investors can impact positively commodity prices, because there is a connection between the risk bearing capacity of broker dealers and risk premia (see Singleton, 2014).

1986 and 1990 the speculative component did play an important role in determining oil prices, however, it is not the case for the oil price surge of 2003-2008.

Kilian also argues that if the perception of the dramatic increase in positions taken by financial investors after 2003 generated speculative pressures on oil futures prices that were transferred to the oil physical market, then inventory demand would have also increased given the arbitrage condition that links both markets, which according to his previous results there is no evidence of speculative demand pressures in the physical oil market after that year. Kilian emphasises that the underlying assumption of having an exogenous behaviour of financial investors with respect to the physical markets is hard to believe because in his opinion it is more plausible that their behaviour is due to their expectations of a persistent economic growth in the emerging markets (see Kilian, 2013).

For Kilian (2013) the difficulty of explaining large recessions based on exogenous oil price shocks is underpinned by the idea that the economy reacts asymmetrically to these shocks, where positive oil price shocks generate large recessions and negative ones have a smaller effect on the economy. Much of the empirical studies focuses on the dynamic responses of oil price shocks, assuming that oil prices are predetermined with respect to domestic real output, which is consistent with the US data and thus linear Vector Autoregressive (VAR) and structural VAR models can be used to quantify the impact of an oil shock in the US economy and also their asymmetric effects. However, these oil innovations reflect global fundamentals in the oil market that affect not only the real price of oil, but also commodity prices and macroeconomic factors, which violates “the everything else constant” assumption to infer causality, and therefore these models do not suffice to understand the dynamic effects of oil price shocks Kilian (2013).

The structural VAR models state that any positive oil price innovation generates a reduction in real output, but this result does not apply at all times, it is correct for the 1970’s but inaccurate for the 2003-2008 period, because the oil price shock is the result of higher demand for oil coming from unexpected global economic growth, in particular from Asian economies.

Kilian indicates that it is necessary to model the sources of growth in the global economy to understand the reasons behind the recent increment in oil prices, rather than considering exogenous oil price shocks. Structural VAR models are also limited in the sense that do not allow to distinguish the origin of the flow demand shocks or if they are driven by productivity or monetary policy shocks, but only average responses.

Other papers have studied the forecasting properties of currencies, in particular commodity currencies. Chen, Roggo and Rossi (2010) offer a robust study about the in -sample (after controlling for parameter instabilities), and out- sample predictability of exogenous commodity currencies in predicting global commodity spot prices. Most of their research is based on nominal exchange rates and the aggregated spot price index from the International Monetary Fund (IMF).

Motivated by Chen.et.al (2010) findings, Groen and Pesenti (2011) also tested the forecasting power of these exogenous exchange rates on commodity price indices. They based their analysis on three approaches (past information of commodity prices and factor-augmented regressions), and compare their results with the autoregressive and random walk models. In a wider exercise, Gargano and Timmerman (2014) study the forecasting properties of financial and macroeconomic predictors for the monthly, quarterly and yearly horizons.

1.2.2 The role of speculation on explaining commodity futures prices

Supporting evidence regarding the role of speculation on explaining the boom of crude oil futures prices is given by Singleton (2014) who argues that supply and demand can explain the dynamic of oil prices during normal times, but during crisis periods fundamental models fail to describe the rise in oil prices and volatilities, as they ignore time varying risks. Suggests other factors beyond fundamentals were key to explain oil price behaviour throughout 2008, in which index-investing and managed money spread positions were an important part on commodity price variations in the context of risk aversion and heterogeneous beliefs, even among the same set of investors about their expectations of economic fundamentals.

According to Singleton to understand the role of inventories, speculation and crude oil prices it is widely believed that if there is a speculative activity which drives oil prices up this must be accompanied by an increase in inventories. Thus, there should be a positive relationship of prices and inventory levels. However, this can also be influenced by the level and assumption of uncertainty of supply and demand.

Moreover, on examining the impact of index-investors on prices it is relevant to observe that the higher co-movement among crude oil futures prices of the one and the two year with nearby futures contracts, and the future prices and equity returns, it is due to an increase in participation of larger investors (hedge funds) in oil futures markets.

Singleton focuses on whether or not the difference in beliefs across investors can induce booms in oil futures prices and higher volatility by changing risk premia (investors learning optimal process conditions by past prices and fundamentals). With his empirical exercise, he aims to find if index- flows[4] have predictive power on crude oil futures markets by obtaining by ordinary least squares (OLS), out of sample predictions of realised returns[5] onto index flows, managed money and other control variables that has been suitable good predictors. His results suggest that during the crisis, imputed index long positions in oil, and spread positions in futures by

[4] Singleton (2014) states that there are three reasons to use index flows to predict futures prices:

1. Generate a variation in prices to balance demand and supply in the futures markets.
2. Risk premiums may depend on information that it is related to these flows.
3. Some organisations based their trading strategies on proprietary order-flow information.

[5] "…Time-series of excess returns over one- and four-week holding periods are computed for futures contracts with maturities of 1, 3, 6, 12, and 4 months. The sample period is from September 12, 2006, through January 12, 2010…". Singleton, K. J. (2014), "The 2008 Boom/Bust in Oil Prices". Management Science 60 (2) , p.309.

managed money carry predictive power in forecasting excess returns, and therefore in predicting oil futures prices.

One study that challenges Singleton´s findings is the one of Hamilton and Wu (2013), who propose a simple model of futures arbitrage that use data on the 12 commodities[6] covered by the Supplemental Commitment of Traders COT[7], to study the role of index-funds and found like former studies that index-fund hardly cause an effect on these 12 agricultural futures prices. The empirical results are negative values of the $\overline{R^2}$ and statistically insignificant coefficients of the estimators for the majority of these commodities.

From Hamilton and Wu´s perspective, the predictive power of imputed positions in crude oil contracts to forecast crude oil premium during the great recession of 2006-2009, it is due more to the endogenous dynamic of index investing during the crisis rather than a systemic predictive power of these imputed positions. The main conclusion is that in line with previous research there is a lack of strong empirical evidence to support the general perception that states that index-fund investment can help to predict excess returns in the future markets, and therefore predict commodity futures prices.

Hamilton and Wu's findings show that Singleton's results are puzzling because the imputed flows from agricultural markets can predict future oil returns (in-sample), but not agricultural prices, and a direct oil measure of index flows do not offer predictive power for the oil markets.

[6] The 12 commodities are beans, wheat, corn, beanoil, cattle, cocoa, coffee, cotton, fedcattle, hogs, KCwheat and sugar.

[7] “The Commodity Futures Trading Commission (Commission) began publishing a Disaggregated Commitments of Traders (Disaggregated COT) report on September 4, 2009. The first iteration of the report covered 22 major physical commodity markets; on December 4, 2009, the remaining physical commodity markets were included”. From Disaggregated Commitments of Traders Report Explanatory Notes CFTC p1.

Another document that criticises Singleton´s evidence is the one of Fattouh, Kilian, and Mahadeva (2012) whose focus relies on the role of speculation in oil markets. As they describe, different strands in the literature have been conducted: one links the bigger participation of financial investors in oil futures markets to evidence the higher co-movement among oil, commodity and stock prices; others aim to establish a causal link between index traders positions and oil futures markets; another wants to see whether higher crude oil spot prices follow in a systemic manner previous increases in crude oil futures prices, a fourth one focuses on the historically negative correlation between oil prices and inventories, structural VAR models to quantify the role of speculation considering the endogeneity of the variables, and finally the role of time varying risk premia in oil futures markets.

In this study Fattouh, Kilian, and Mahadeva (2012) argue that financial investors behaviour reflects a fundamental perception of the crude oil markets, thus, to identify causality in financial markets one needs structural models. Since futures and spot oil prices are determined simultaneously and are conducted by the same driving forces, primarily shifts in the demand for commodities. They argue that even though index funds positions could carry predictive power in forecasting oil futures prices, that does not necessarily mean causality; and the main question is if these investors were acting endogenously to the economy (higher economic growth which leads to higher hedging demand) or exogenously and triggered the oil futures prices.

Challenging the financialization argument Kilian and Lee (2013) aim to quantify the speculative component in the real price of crude oil by estimating Vector Autoregressive VAR models which use monthly data[8], based on Kilian and Murphy work (the structural oil market model) but using two different measures of oil inventories: Kilian and Murphy´s proxy constructed from available data from the Energy Information Administration (EIA), and a new proxy of crude oil stocks

[8] The VAR models used by Kilian and Lee (2013) are based on 4 variables: the percent change in global crude oil production, as reported by the U.S. Energy Information Administration; a measure of cyclical fluctuations in global real economic activity proposed by Kilian (2009), the real price of crude oil (obtained by deflating the U.S. refiners' acquisition cost for crude oil imports by the U.S. CPI), and the change in above-ground global crude oil inventories (original proxy, and the proxy from EIG, speculative demand shock). These VAR models use seasonal dummies and 24 autoregressive lags.

provided by the *Energy Intelligence Group* (EIG) (having the advantage of a wider scope and capturing to some extent China and India crude oil storage) to support the argument that the measure of world crude oil inventories oils matters and can lead to different results in quantifying the speculative demand shocks and explaining the surge of crude oil prices during the past decade.

The estimation methodology of the VAR models is that used in Kilian and Murphy (2012). The dependent variable is the seasonally adjusted real price of oil in percent deviations from its mean, estimating the reduced-form model by OLS, analysing 5 million potential structural models, and keep the ones which meet the identifying requirements (with price elasticity of oil demand nearest to the benchmark -0.26), showing the robustness of their studies.

From one side they run these VAR models using the original proxy of crude oil inventories, and the new proxy EIG to estimate the real price of oil. Estimating the cumulative changes in the real price of oil caused by any of the following shocks: the flow supply, the flow demand, and the speculative demand shocks over a determined period of time (see Kilian and Murphy, 2012).

Kilian and Murphy (2012) findings illustrate that for their subsampled periods the increase in the real price of crude oil was overall due to the cumulative effect of the flow demand shocks, which are associated with the global business cycle, and there is no evidence of speculative shocks having a major effect in the surge of oil prices since 2003. They also find evidence that speculation might lower the real price of oil.

1.2.3 MIDAS framework and commodity price forecasting

To deal with time series data with mixed frequencies, Armesto, Engemann, and Owyang (2010) argue that the researcher has different methods: the most popular is simple time averaging the higher-frequency data (each of the slope coefficients of each individual observation sampling of X are equal), the step-weighting function (each of the slope coefficients sampling of X are exclusive) so that one can work with the right and left hand side of data at the same frequency; and a more modern framework introduced by Ghysels, Santa Clara and Valkanov (2004): Mixed Data Sampling MIDAS Framework, which is a parsimonious way of exploiting the high-frequency data, by allowing to estimate regressions without the need of sampling the variables at the same frequency, by the use of different polynomials as weighting functions to estimate hyperparameters. To estimate univariate MIDAS models the researcher projects a lower-frequency variable onto its past values, and the lags of an exogenous higher -frequency variable.

Forecasting lower-frequency variables when dealing with monthly, quarterly and annual data the simple time averaging method can be useful, but when using higher-frequency data (daily or intra-daily) as predictors the step weighting function could result in parameter proliferation, especially for models with more explanatory variables because the sampling rate increases with higher-frequent data like daily data. Therefore, Armesto, Engemann, and Owyang (2010) aim to measure the effectivity even among these three forecasting methods (simple averaging, step-weighting function, and the exponential Almon Polynomial MIDAS), by comparing the root-mean squared errors RMSE among the three.

Their findings show that for all horizons the time-averaging and MIDAS models perform similarly, however, MIDAS models also preserve timing information apart from being parsimonious. Nevertheless, the conclusion is that none of the three methods is consistently superior to the other, and their effectivity depends on the nature of the data and available information.

For further extensions regarding MIDAS framework Ghysels, Synko and Valkanov (2007) documented an empirical analysis based on previous financial literature risk-return trade-off and volatility (variance) forecasting, by looking at the risk-return (regressing market volatility onto excess returns) at different weekly frequencies and use other polynomial specification and many predictors that have been proved to carry predictive power in forecasting volatility in a MIDAS framework (regression of lower frequency data onto higher-frequency data), and test other variables.

Their findings show a positive and statistically-significant risk-return trade off across horizons and predictors, and that the variables which predict better the variance could correspond to a part of the variance which is not related to excess returns, because by using these predictors they do not obtain better forecasts for excess returns. As well they find a negative impact in volatility forecasting of using high-frequency data, microstructure noise. Some documents such as Marsilli (2016) have shown that MIDAS methodology has provided more accurate out of sample forecasts when forecasting macroeconomic variables, as long as the left and right hand side frequencies variables are not very dissimilar.

Therefore, some researchers have found it plausible to extend the use of MIDAS framework to forecast commodity prices. The literature which is available has studied the potential contributions of the use of high-frequency data on forecasting commodity prices, in particular crude oil and corn spot prices for the US markets. In this regard, Baumeister, Guérin, and Kilian (2014) use mixed-frequency data modelling (vector autoregressive (MF-VAR)[9] and MIDAS models) to measure the benefits of using higher-frequency financial data (forward-looking information) and U.S. energy markets data (sampled weekly or daily), to identify what regressors from a specific set[10] carry more predictive power in forecasting monthly oil prices: the real U.S. refiners acquisition cost for crude oil imports (widely used proxy for the global price of oil).

To forecast the monthly prices of oil h-months- ahead, from 1 to 24, Baumeister, Guérin, and Kilian (2014) estimate MIDAS regressions using weekly financial data

[9] MF-VAR refers to mixed-frequency vector autoregressive model.

[10] The group of eight higher-frequency predictors is constituted by “the spread between the spot prices of gasoline and crude oil; the spread between the oil futures price and the spot price of crude oil; cumulative percent changes in the Commodity Research Bureau (CRB) index of the price of industrial raw materials, U.S. crude oil inventories, and the Baltic Dry Index (BDI); returns and excess returns on oil company stocks; cumulative changes in U.S. nominal interest rates (LIBOR, federal funds rate), and cumulative percent changes in the U.S. trade-weighted nominal exchange rate” Baumeister, Guérin, and Kilian (2014, p.2)

(constructed from daily data) on the right-hand side of the equation. Assessing the efficacy of the MIDAS forecast comparing the Mean Squared Prediction Errors MSPE, and directional accuracy of the MIDAS models with the no-change forecast and the monthly models as benchmarks.

Their findings confirm results from forecasting literature where there is no a major gain on forecasting accuracy from using high frequency data directly to forecast monthly oil prices. Because, despite MIDAS specifications can provide better forecasts than the benchmarks, they do not do it in a systematic manner; and the models based on monthly financial predictors[11] sometimes beat the MIDAS models. Nevertheless, one important empirical finding is that it is possible to forecast the price of oil in real time, and that the U.S. oil inventories plays a major role as a strong predictor of oil prices, regardless of the model.

Etienne (2015) tests if commodity markets financialization impacts the spot price of corn in U.S.A (average prices of corn received by farmers US National Agricultural Statistics Service NASS). The motivation of this study is different from that in Singleton (2014) which looks at the effect of commodity index investors (from intermediate term growth rate of index positions and manage money spread positions) on commodity future markets (oil future markets not spot ones), whose channel of transmission to the spot markets may differ from the futures markets, Hamilton and WU (2013).

Etienne by contrasts aims to assess if high-frequency financial data is useful to predict agricultural monthly spot prices[12] using univariate MIDAS models following Ghysels, Santa Clara and Valkanov (2004), specifically ADL MIDAS (ALMON

[11] Models based on returns on oil stocks, gasoline price spreads, and oil futures prices.

[12] Etienne (2015) used financial variables at daily frequency which are the Baltic Dry Index (BDI indicator or global real economic activity), the nominal trade-weighted U.S dollar index in terms of major currencies, 3-month Treasury bill interest rate, nearby WTI crude oil futures prices, and S&P500. Which can carry predictive power in forecasting commodity prices, according to recent studies, see for instance Gargano and Timmermann (2014).

exponential MIDAS) and EMIDAS (equally weighted MIDAS models) compared with benchmark models, the no-change forecast (or random walk) and Autoregressive AR (1) models. To compare the forecasting accuracy[13] of the models for the periods 1995-1999, 2000-2004, 2005-2009 and 2010-2014 he computes the MSPE by using the Clark and West CW test, and the success ratio to assess the predicting directional changes accuracy.

In line with previous findings, Etienne´s evidence concludes there is no consistent superiority on the forecasts when comparing with random walk and autoregressive models, which suggests that spot corn prices in US are efficient and past information contains the majority of information from financial markets, even for the periods where financial markets are correlated with commodity prices, in contrast to Singleton (2014), where he argues that during crisis financial investor flows carry predictive power on forecasting oil futures prices.

1.3 Data

The S&P GSCI spot index (Goldman Sachs Commodity Index) measures physical commodity spot prices, which is a world-production and contract production weighted and tradable index considered as a benchmark for commodity markets and global inflation. The S&P GSCI spot index represents the price levels of designated contracts of 24 commodities. It considers the first nearby contract expirations and roll contract expirations of agriculture, livestock, metals and energy prices S&P Dow Jones Indices (2016) [14].

The high-frequency predictors are based on the previous literature available on a daily frequency rate. Given the impact of the US monetary policy on commodity

[13] Etienne (2015) uses a rolling window of 120 observations to forecast one-month ahead forecasts for each of the four models.

[14] The S&P GSCI considers the rolling procedure an investor follows since he/she sells the first nearby contracts and needs to buy the second nearby contracts as delivery date is nearer (or the subsequent contracts based on liquidity). The roll period is from the fifth to the ninth business day (see S&P Dow Jones Indices, 2016).

markets short –term interest rates are relevant, in particular the 3 month -Treasury bill rate from the secondary market (tbill). the Baltic Dry Index (BDI) as a measure of the global business cycle.

Based on the findings of Chen, Rogoff and Rossi (2010) I consider the following nominal exchange rates due to their exogeneity and forward looking features[15]: Chilean peso, Canadian dollar, Australian dollar, New Zealand dollar and South African Rand[16].

To consider hedging demand Managed Money Spreading Positions (hedge funds) for grains: wheat, corn and soybeans are included based on Singleton's findings (2014). These positions are available for 22 agricultural commodity future markets from the weekly disaggregated Futures Commitments of Traders (COT) reports[17] starting on June 13, 2006. Four categories of traders are reported: Producer/Merchant/Processor/User; Swap Dealers; Managed Money; and Other Reportables.

Singleton (2014) uses the lagged 13-week change of index traders and managed money positions to assess the possible impact of speculation on the oil futures markets. Hamilton and Wu (2013) aim to replicate Singleton's findings focusing their analysis on the agricultural futures markets by using a direct measure of index-fund positions. Therefore, following their studies I constructed the log of managed money spread notional exposure to examine if these speculative positions of wheat, corn, soybeans and a weighted average grains measure, add predictive power on the S&P SCGI monthly returns in the mixed frequency data framework and the monthly models.

[15] These currencies are exogenous due to their small power in the international markets.

[16] From Bloomberg, Central Bank of Chile and the Board of Governors of the Federal Reserve System.

[17] "The Commodity Futures Trading Commission (Commission) began publishing a Disaggregated Commitments of Traders (Disaggregated COT) report on September 4, 2009. The first iteration of the report covered 22 major physical commodity markets; on December 4, 2009, the remaining physical commodity markets were included". From Disaggregated Commitments of Traders Report Explanatory Notes CFTC p1.

Hamilton and Wu (2013) study the predictability of index-traders notional exposure on weekly agricultural futures commodity returns (r_t) for 12 agricultural commodities.

$$r_t = \alpha_1 + \phi_1 r_{t-1} + \pi_1 \tilde{x}_{\cdot t-1} + \varepsilon_{1t}$$

Where α_1 defines the constant parameter

$\phi_1 r_{t-1}$ corresponds to the autoregressive component AR(1)

$\pi_1 \tilde{x}_{\cdot t-1}$ denotes the one period lagged log index-investors' notional exposure
ε_{1t} is the error term.

Hamilton and Wu (2013) conduct their study based on long positions held by commodity index traders (notional exposure by expressing it in number of contracts), the majority of which correspond to swap dealers. By contrast, my analysis is focused on the managed money spreading positions applying their equation to compute the speculative positions for wheat, corn, soybeans and a weighted average of a grains measure by accounting the corresponding weights of the S&P SCGI (2016) methodology, with this measure I try to capture grains movements in one time series.

For the mixed data frequency models (MIDAS) I use the weekly positions and for the monthly models the simple monthly average.

Hamilton and Wu (2013) define log of index-positions with the next formula, which I adapted for my study:

$$\tilde{x}_{\cdot t} = 100(\ln x_t + \ln F_t)$$

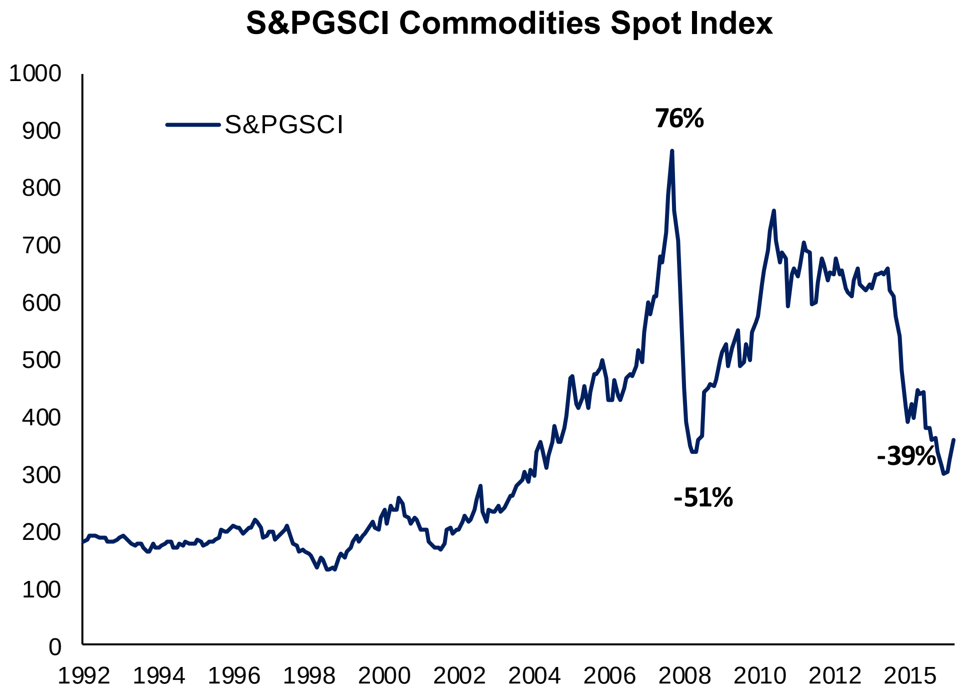
where $\tilde{x}_{\cdot t}$ refers to the ln of managed money's notional exposure.

$\ln x_t$ is the ln of spreading managed money positions in number of contracts

$\ln F_t$ is the ln of the futures last price of the nearby contract of the corresponding grain on each Friday when the CFTC publishes the futures markets positions.

I treated missing futures data as a simple average of the previous and following week futures commodity price.

Graph 1



Source: Bloomberg

Table 1a

Data	Frequency	Start Date	Unit
SPGCCI Commodity Index spot	Daily	01/02/1970	Value:US Dollar
Baltic Dry Index	Daily	04/01/1985	Value:US Dollar
3-month Treasury bill secondary market rate discount basis	Daily	04/01/1954	Percent per year: US dollar
Canadian Dollar Spot	Daily	04/01/1971	1 USD in CAD
Australian Dollar Spot	Daily	04/01/1971	1 AUD in USD
New Zealand Dollar Spot	Daily	04/01/1971	1 NZD in USD
Chilean Peso Observed	Daily	02/01/1984	1 USD in CLP
South African Rand Spot	Daily	04/01/1971	1 USD in ZAR

Source: Bloomberg, Central Bank of Chile, and Board of Governors of the Federal Reserve System.

Disaggregated Commitment of Traders- Futures Only

Table 1b

CFTC	Number of Futures
Agriculture Total	**22**
Contracts included in the S&P SCGI (2016)	**11**
Grains	**4**
WHEAT-SRW - CHICAGO BOARD OF TRADE	
WHEAT-HRW - CHICAGO BOARD OF TRADE	
CORN - CHICAGO BOARD OF TRADE	
SOYBEANS - CHICAGO BOARD OF TRADE	

Mananaged Money spreading positions.
Data available since June 13 2006.
Source: U.S Commodity Futures Trading Comission (CFT).

1.4 Methodology: univariate MIDAS models and forecasting combinations

In order to preserve useful information from high-frequency variables Ghysels, Synko, and Valkanov (2007) present Mixed Data Sampling MIDAS regression models, which provide a flexible and parsimonious way to present relations among lower-frequency data regressed onto higher-frequency data. In their study they actually capture a set of dynamics that would be otherwise hard to get.

“The Simple MIDAS model”

$$y_t = \beta_0 + \beta_1\, B\left(L^{\frac{1}{m}};\theta\right) x_t{}^{(m)} + \varepsilon_t{}^{(m)} \qquad (1)$$

For t=1,…,T; where $B\left(L^{\frac{1}{m}};\theta\right) = \sum_{k=0}^{K} B(k;\theta)L^{k/m}$ and $L^{1/m}$ is a lag operator such that $L^{1/m}x_t{}^{(m)} = x_{t-1/m}{}^{(m)}$; the lag coefficients in $B(k;\theta)$ of the lag operator $L^{k/m}$ are parameterized as a function of a small dimensional vector of parameters θ.”[18] This vector of parameters θ is to avoid parameter proliferation. The parameter β_1 captures the full impact of lagged $x_t{}^{(m)\prime}s$ on y_t. By normalizing the function $B\left(L^{\frac{1}{m}};\theta\right)$ to sum to unity one can identify the parameter β_1.

The advantage of the parameterizations that are proposed by Ghysels, Synko, and Valkanov (2007) allow to deal directly with the lag selection. For different estimated $\theta' s$ the parameterized weights can decline at different speeding when the number of lags on the $x_t{}^{(m)\prime}s$ increases. Therefore, the data itself selects the number of lagged $x_t{}^{(m)\prime}s$ that are included in the equation 1, because the rate of decline of the parameterized weights selects the necessary lags to explain the relationship among the $x_t{}^{(m)\prime}s$ on y_t in a mixed frequency context. By contrast in the unrestricted

[18] From Ghysels, E., Synko, A., and Valkanov, R. (2007), “MIDAS regressions: further results and new directions”, Econometric Reviews, 26(1), 54 p.

case the lag selection procedure can lead to include a larger number of lags that ultimately lead to a non- parsimonious specification.

Two popular finite polynomial specifications that parameterize the lag structure of the high-frequency variables $B(k;\theta)$ from equation 1 are exponential Almon and beta lag polynomials due to their flexible ability to take various shapes with the estimation of only a few parameters of θ. Restricting the estimated weights of these polynomial specifications to sum to unity it is possible to identify the parameter β_1. These specifications also provide positive weights which are relevant particularly in volatility modelling. Ghysels (2015) defines polynomial specifications in the following way:

1.4.1 Exponential Almon MIDAS polynomial specification

A simple case of a normalized exponential Almon lag polynomial specification is the one which requires only two parameters. The estimation of θ_1, θ_2 comes from the data set itself.

For two parameters θ_1, θ_2 for the unrestricted (u) and restricted (r) cases

$$B(k;\theta) = w_i^u = w_i(\theta_1, \theta_2) = \frac{e^{\theta_1\ i + \theta_2 i^2}}{\sum_{i=1}^{N} e^{\theta_1\ i + \theta_2 i^2}}$$

$$w_i^r = w_i(\theta_1 0)$$

N represents the number of lags for the high-frequency data.

Equal weights are defined in the case of $\theta_1 = \theta_2 = 0$

1.4.2 Beta polynomial specification

The Beta function as in the exponential Almon lag polynomial the rate of decline indicates the number of lags that must be included in the MIDAS regression.

For three parameters $\theta_1, \theta_2, \theta_3$ the normalized beta probability density function, unrestricted and restricted with non-zero and zero last lag.

$$w_i^{u,nz} = w_i(\theta_1, \theta_2, \theta_3) = \frac{x_i^{\theta_1 -1}(1-x_i)^{\theta_2 -1}}{\sum_{i=1}^{N} x_i^{\theta_1 -1}(1-x_i)^{\theta_2 -1}} + \theta_3$$

$$w_i^{r,nz} = w_i(1, \theta_2, \theta_3)$$

$$w_i^{u,z} = w_i(\theta_1, \theta_2, 0)$$

$$w_i^{r,z} = w_i(1, \theta_2, 0)$$

Where $x_i = (i-1)/(N-1)$

Equal weights are defined in the case of $\theta_1 = \theta_2 = 1$

1.4.3 Unrestricted MIDAS specification

By not restricting the coefficients of the MIDAS model as proposed by Foroni, Marcellino and Schumacher (2015), one can estimate the parameters by the ordinary least squares method since the model is linear in α_i. Therefore, obtaining the Unrestricted MIDAS model:

$$y_t = \beta_0 + \beta_1 \sum_{i=o}^{N-1} \alpha_i x_{t-i/N}{}^{(m)} + \varepsilon_t{}^{(m)}$$

Univariate MIDAS model

The MIDAS specification to forecast the ln returns of a global measure of commodity spot price index for the univariate case is defined as following, the estimated weights are done by the exponential Almon and Beta lag polynomials.

$$S\&P\ GSCI_t = \beta_0 + S\&P\ GSCI_{t-1} + \beta_1\, B\left(L^{\frac{1}{m}}; \theta\right) x_t{}^{(m)} + \varepsilon_t{}^{(m)} \qquad (2)$$

Where

S&P $GSCI_t$ is the returns of commodity spot price index end-of-month official closing prices denominated in US dollars.

${x_t}^{(m)}$ is the daily regressor from table 1a and 1b

The Model parameters of $B\left(L^{\frac{1}{m}};\theta\right)$ are estimated for the rolling and recursive windows by non-linear least squares for the exponential Almon and Beta lag polynomial specifications. Otherwise ordinary least squares (OLS) is used.

1.4.4 Forecasting estimation

1.4.4.1 MIDAS forecasting

$$\widehat{S\&PGSCIret}_{t+1}^{F} = \widehat{\beta_0} + \widehat{\mu_0}\, S\&PGSCIret_t{}^{F} + \widehat{\beta_1}\, B\left(L^{\frac{1}{m}};\hat{\theta}\right) {x_t}^{(m)} + {\hat{\varepsilon}_{t+1}}^{(m)} \qquad (3)$$

F denotes the frequency of the low-frequency variable which is the monthly ln return, using the end of month close price.

(m) corresponds to the frequency of the high-frequency regressor from the set of financial and speculative variables, which is daily (20 business days) for the former and weekly for the latter.

The forecasting equation is similar to the one of Hamilton and Wu (2013) but in the mixed data framework.

1.4.4.2 Monthly model (benchmark)

The most common approach to deal with mixed frequencies is to average the higher-frequency data so that the right-hand side of the equation is sampled at the same frequency of the left-hand side.

The aim is to estimate by the OLS method the parameters β of the next equation for each rolling window

$$y_{t+1} = \beta_0 + \boldsymbol{X}_t\,\boldsymbol{\beta} + \varepsilon_t$$

Where $\boldsymbol{y_{t+1}}$ denotes the monthly log return of the S&PGSCI and $\boldsymbol{x_t}$ the regressor is the monthly average of managed money spreading positions for the four grains measures from the data section.

Therefore the forecasting monthly model is

$$S\&PG\widehat{SCI}ret_{t+1} = \widehat{\beta_0} + \boldsymbol{X_t}\,\widehat{\boldsymbol{\beta}} + \widehat{\varepsilon_{t+1}} \tag{4}$$

The monthly log return denotes the return of the end of month close price, and each of the independent variables X_t from the data section is defined in monthly averages.

$\boldsymbol{X}_t$ denotes the vector of lagged managed money spreading positions, which includes $\boldsymbol{x_t}$, $\boldsymbol{x_{t-1}}$, and $\boldsymbol{x_{t-2}}$.

1.4.4.3 Forecasting combinations

There is an agreement on the literature regarding the use of forecasting combinations to improve forecasting accuracy. The forecasting combinations were computed following Ghysels (2015).

For the one- step ahead forecast:

If $S\&\widehat{PG}SCIret^F_{i,t+1/t}$ corresponds to the i^{th} individual out-of-sample forecast of $S\&PGSCIret^F_{i,t+1/t}$ at time t. The forecast combination at time t is a weighted average of k individual 1-step ahead out-of-sample forecasts, ($S\&PGSCIret^F_{1,t+1/t}, \ldots, S\&PGSCIret^F_{k,t+1/t}$), given as:

$$F\ S\&\widehat{PG}SCIret^F_{cM,t+1/t} = \sum_{i=1}^{k} w_i^1, S\&\widehat{PG}SCIret^F_{i,t+1/t} \tag{5}$$

Where $(w_{1,t}^{1},\dots,w_{k,t}^{1})$ is the vector of combination weights at time t, whose combined forecast depends on the class of model that generated each forecast. For the present study, the class of model is defined by different high-frequency series with each individual forecast $S\&PGSCIret_{i,t+1/t}^{F}$ produced by the MIDAS regression with the same polynomial and lag lengths for the right and left hand side variables.
(The different high-frequency series were chosen based on the efficiency of the univariate MIDAS model compared to the benchmark AR(1)).

The weighting ways:

Equally weighted weights $w_{i,t} = 1/n$

BIC-weighted forecast $w_{i,t} = \frac{\exp(-BIC_i)}{\sum_{i=1}^{n}\exp(-BIC_i)}$

MSFE-related model averaging

$$w_{i,t} = \frac{m_{i,t}^{-1}}{\sum_{i=1}^{n} m_{i,t}^{-1}}$$

$$m_{i,t} = \sum_{i=T_0}^{t} \delta^{t-i}\left(S\&PGSCIret_{s+1/t}^{F} - S\&\widehat{PGS}CIret_{i,s+1/s}^{F}\right)^2$$

Where T_0 is the first out-sample observation, $S\&\widehat{PGS}CIret_{i,s+1/s}^{F}$ is the out- sample forecast, and δ is the exponential averaging parameter.

MSFE averaging $\delta = 1$
DMSFE averaging $\delta = .9$ for the discounted MSFE

1.5 Empirical Results

1.5.1 Financial variables and commodity currencies

In order to assess any improvement to the monthly S&PGSCI return forecasts relative to the AR (1) benchmark by means of high frequency financial variables and commodity currencies. I test individually the following daily predictors, the 3-month Treasury bill, the Baltic Dry Index, and the exchange rates -relative to the US dollar- of Canada, New Zealand, South Africa, Australia and Chile. Alike previous studies, I compute for the period 2000-2016 the one-step ahead out of sample MIDAS S&PGSCI monthly return forecast and their respective Root Mean Squared Error (RMSE) as a measure of forecasting accuracy, comparing this RMSE to the RMSE obtained from the Autoregressive forecasts.

The reasons why I did not evaluate the statistical significance of the RMSE obtained Diebold Mariano test (DM) it is from one side due to a parameter estimation uncertainty and from the other because this test is based on the population rather than the out of sample forecast MSE of MIDAS models as stated by Baumeister, Guérin, and Kilian (2014). In addition, Diebold (2013) states that the DM test assesses the significance of predictive superiority measure by the MSE, the assumptions of the DM test must hold for the validity of the test. In this particular case the functional form of MIDAS models is not linear whereas the functional form of the benchmark AR(1) is linear.

The MIDAS forecasting model is described by Equation 3 in section 5.4.1. and it is computed for the exponential Almon, Beta lag, and unrestricted lag polynomial specifications. The estimation of the mixed sampling models is done either recursively or in a rolling window of length five year.

The RMSE of the one-step ahead out of sample commodity return forecast generated from univariate financial MIDAS models which follow the rolling window method are computed and compared with the RMSE from the AR(1) benchmark. The sample period is divided as follows: the pre-crisis 2000-2005, crisis 2006-2009 and post-crisis 2010-2016. Tables 2 and 3 illustrate the individual forecasting accuracy of the 3-month treasury bill, the Baltic Dry Index and the five exchange rates of Canada, Australia, New Zealand, South Africa and Chile.

Over the monthly horizon, Table 2 shows that the forecasting accuracy of the MIDAS models tends to be better for the pre-crisis 2000-2005 period, in particular the Canadian dollar offers similar forecasts to the autoregressive estimation, but for the crisis period 2006-2009 the RMSE of this currency worsens the most relative to the Baltic Dry Index and overall to the 3 month-treasury bill rate.

Table 2

RMSE's 1-step ahead forecast (out-sample forecast), rolling window*

MIDAS models vs benchmark AR(1)

Periods	RMSE	3-Month tb [1/]	BDI [2/]	CAD [3/]	3-Month tb [1/]	BDI [2/]	CAD [3/]
	Beta	0.069	0.066	0.069	105	100	105
2000-2005	Exp Almon	0.068	0.068	0.069	103	102	105
	U-MIDAS	0.072	0.075	0.073	109	114	111
	AR(1)	0.066	0.066	0.066	100	100	100
	Beta	0.086	0.090	0.092	104	109	112
2006-2009	Exp Almon	0.085	0.087	0.087	103	105	105
	U-MIDAS	0.129	0.119	0.101	155	144	122
	AR(1)	0.083	0.083	0.083	100	100	100
	Beta	0.064	0.069	0.064	101	108	101
2010-2016	Exp Almon	0.063	0.069	0.067	99	108	104
	U-MIDAS	0.065	0.077	0.072	102	120	112
	AR(1)	0.064	0.064	0.064	100	100	100

*Parameter estimation rolling window starts at window Jan 1995-Dec1999.
AR (1) 1 step-ahead forecast.
Ratios under 100 show that the MIDAS forecasts outperform the benchmark AR(1).
[1/] Univariate MIDAS monthly S&PGSCI return onto the lagged return and daily 3-Month Treasury Bill annual percentage rate.
[2/] Univariate MIDAS monthly S&PGSCI return onto the lagged return and the daily Baltic Dry Index.
[3/] Univariate MIDAS monthly S&PGSCI return onto the lagged return and the Canadian dollar US terms.

Similarly, Table 3 displays the RMSE of the one step-ahead out- of sample forecast for the rest of the commodity currencies: Australian dollar, New Zealand dollar, South African rand and Chilean peso. These results suggest that during the crisis period the New Zealand dollar and the South African rand tend to perform better compared to the financial variables of the previous figure, and particularly relative to the MIDAS model specifications of table 3 in the post crisis period, however, the accuracy of the AR(1) model is still better in almost all cases apart from the MIDAS specifications that include the Chilean peso as a predictor. It is interesting that the Chilean peso is the only currency that helps to improve the forecast during the crisis and post crisis periods. The RMSE is reduced by 8 and 3 percent respectively compared to the benchmark AR(1).

Table 3

RMSE's 1-step ahead forecast (out-sample forecast), rolling window*						MIDAS models vs benchmark AR(1)			
Periods	**RMSE**	**AUD [1/]**	**NZD [2/]**	**ZAR [3/]**	**CLP [4/]**	**AUD [1/]**	**NZD [2/]**	**ZAR [3/]**	**CLP [4/]**
	Beta	0.068	0.068	0.068	0.068	103	103	103	104
2000-2005	Exp Almon	0.070	0.069	0.068	0.072	106	104	103	109
	U-MIDAS	0.072	0.076	0.077	0.075	109	115	117	113
	AR(1)	0.066	0.066	0.066	0.066	100	100	100	100
	Beta	0.088	0.083	0.084	0.076	106	100	102	92
2006-2009	Exp Almon	0.094	0.083	0.088	0.086	114	101	106	104
	U-MIDAS	0.095	0.094	0.107	0.087	115	114	129	105
	AR(1)	0.083	0.083	0.083	0.083	100	100	100	100
	Beta	0.064	0.066	0.067	0.068	101	103	105	107
2010-2016	Exp Almon	0.067	0.070	0.065	0.062	106	109	102	97
	U-MIDAS	0.072	0.074	0.071	0.070	112	116	112	109
	AR(1)	0.064	0.064	0.064	0.064	100	100	100	100

*Parameter estimation rolling window starts at window Jan1995-Dec1999.
AR(1) 1 step- ahead forecast.
Ratios under 100 show that the MIDAS forecasts outperform the benchmark AR(1).
[1/] Univariate MIDAS monthly S&PGSCI return onto the lagged return and the Australian dollar US terms.
[2/] Univariate MIDAS monthly S&PGSCI return onto the lagged return and the New Zealand dollar US terms.
[3/] Univariate MIDAS monthly S&PGSCI return onto the lagged return and the South African Rand US terms.
[4/] Univariate MIDAS monthly S&PGSCI return onto the lagged return and the Chilean peso US terms.

The forecasts obtained by estimating recursively the MIDAS models show more RMSE reductions compared to the ones generated by the rolling window method. As illustrated on Tables 4 and 5, during the crisis period 2006-2009 and 2007-2009 for each table respectively, models that include the Baltic Dry Index outperform by 3 percent the AR(1) forecasts, whereas the 3-month Treasury bill, the Australian and the New Zealand dollars offer a slightly better one percent improvement relative to the benchmark.

During the post-crisis the Chilean peso, the South African Rand and Canadian dollar tend to offer better forecasts than the autoregressive process. For the period 2010-2016, table 4 shows that incorporating the Canadian dollar into the MIDAS estimation reduce the RMSE in 1 percent. As displayed on table 5 for the period 2006-2009, the MIDAS models estimated recursively which include currencies as predictors slightly improve the forecasting accuracy by 1% relative to the forecasts of the autoregressive process. While for the most recent period 2010-2016 the MIDAS models that include the Chilean peso as a regressor are the only ones registering and RMSE reduction of 1% of magnitude.

Table 4

RMSE's 1-step ahead forecast (out-sample forecast), recursive window* | MIDAS models vs benchmark AR(1)

Periods	RMSE	3-Month tb [1/]	BDI [2/]	CAD [3/]	3-Month tb [1/]	BDI [2/]	CAD [3/]
	Beta	0.069	0.068	0.069	104	102	103
2000-2005	Exp Almon	0.068	0.068	0.069	102	102	104
	U-MIDAS	0.073	0.070	0.070	109	106	106
	AR(1)	0.066	0.066	0.066	100	100	100
	Beta	0.082	0.087	0.088	99	106	107
2006-2009	Exp Almon	0.084	0.080	0.085	101	97	103
	U-MIDAS	0.083	0.100	0.092	100	122	111
	AR(1)	0.082	0.082	0.082	100	100	100
	Beta	0.061	0.066	0.060	100	108	99
2010-2016	Exp Almon	0.061	0.067	0.063	100	110	104
	U-MIDAS	0.061	0.069	0.065	100	114	108
	AR(1)	0.061	0.061	0.061	100	100	100

*Parameter estimation recursive window starts at window Jan 1995-Dec1999.
AR (1) 1 step-ahead forecast.
Ratios under 100 show that the MIDAS forecasts outperform the benchmark AR(1).
[1/] Univariate MIDAS monthly S&PGSCI return onto the lagged return and daily 3-Month Treasury Bill annual percentage rate.
[2/] Univariate MIDAS monthly S&PGSCI return onto the lagged return and the daily Baltic Dry Index.
[3/] Univariate MIDAS monthly S&PGSCI return onto the lagged return and the Canadian dollar US terms.

Table 5

RMSE's 1-step ahead forecast (out-sample forecast), recursive window* | MIDAS models vs benchmark AR(1)

Periods	RMSE	AUD [1/]	NZD [2/]	ZAR [3/]	CLP [4/]	AUD [1/]	NZD [2/]	ZAR [3/]	CLP [4/]
	Beta	0.069	0.068	0.068	0.067	104	103	102	102
2000-2005	Exp Almon	0.069	0.068	0.067	0.069	104	102	101	105
	AR(1)	0.066	0.066	0.066	0.066	100	100	100	100
	Beta	0.081	0.081	0.086	0.082	99	99	104	99.8
2006-2009	Exp Almon	0.085	0.085	0.084	0.083	103	103	102	100
	AR(1)	0.082	0.082	0.082	0.082	100	100	100	100
	Beta	0.061	0.061	0.061	0.060	101	101	101	99
2010-2016	Exp Almon	0.061	0.061	0.061	0.061	101	101	100	100
	AR(1)	0.061	0.061	0.061	0.061	100	100	100	100

*Parameter estimation recursive window starts at window Jan1995-Dec1999.
AR(1) 1 step- ahead forecast.

Ratios under 100 show that the MIDAS forecasts outperform the benchmark AR(1).
1/ Univariate MIDAS monthly S&PGSCI return onto the lagged return and the Australian dollar US terms.
2/ Univariate MIDAS monthly S&PGSCI return onto the lagged return and the New Zealand dollar US terms.
3/ Univariate MIDAS monthly S&PGSCI return onto the lagged return and the South African Rand US terms.
4/ Univariate MIDAS monthly S&PGSCI return onto the lagged return and the Chilean peso US terms.

It is often thought that forecast combinations improve forecasting performance see for instance Chen, Rogoff and Rossi (2010). For the same forecasting period 2000-2016 the forecast combinations of two univariate MIDAS models were computed[19]. Tables 6 and 7 portray the comparison of the RMSE obtained by estimating equation 5 to generate the forecasting combinations of two univariate MIDAS models which include either a commodity currency or a financial variable.

Table 6 and 7 show that forecast combinations of MIDAS models including either the Canadian dollar or the Baltic Dry Index, and the forecast combination of MIDAS estimations that consider the Australian dollar or the 3-Month Treasury bill can be at most as efficient as the variable with the lower RMSE, except for the crisis period 2006-2009 where the forecast combination of the Cad and BDI models slightly lowers the RMSE relative to the efficiency of the MIDAS model that only considers the BDI.

In general, the beta lag polynomial specification offers less inaccurate forecasts compared with the exponential Almon. Despite the fact that the forecast combinations tend to be more similar to the AR (1) benchmark during the pre-crisis period 2000-2005, the RMSE MIDAS model combinations worsens during the crisis period 2006-2009, and slightly improve for the most recent period 2010-2016.

[19] These results come from my first attempt to forecast the monthly S&PGSCI return using MIDAS models with a rolling window that starts at window Jan 1992-Dec1999.

Table 6

RMSE's 1-step ahead forecast (out-sample forecast), rolling window*				MIDAS models vs benchmark AR(1)	
Periods	RMSE	Forecast Exp Almon	Forecast Beta	Forecast Exp Almon	Forecast Beta
	Model1 (Cad)	0.070	0.066	106	101
2000-2005	Model2(BDI)	0.068	0.068	103	104
	Combined by MSFE	0.068	0.067	103	101
	Combined by DMFSE	0.068	0.066	103	101
	Combined by AIC	0.070	0.066	106	101
	Combined by BIC	0.070	0.066	106	101
	Combined by EW	0.068	0.067	103	101
	AR(1)	0.066	0.066	100	100
2006-2009	Model1 (Cad)	0.086	0.089	108	112
	Model2(BDI)	0.082	0.086	103	108
	Combined by MSFE	0.082	0.084	103	106
	Combined by DMFSE	0.082	0.085	103	107
	Combined by AIC	0.086	0.089	108	112
	Combined by BIC	0.086	0.089	108	112
	Combined by EW	0.082	0.084	104	106
	AR(1)	0.079	0.079	100	100
2010-2016	Model1 (Cad)	0.065	0.064	110	109
	Model2(BDI)	0.065	0.061	111	104
	Combined by MSFE	0.064	0.061	110	104
	Combined by DMFSE	0.064	0.061	110	104
	Combined by AIC	0.065	0.064	110	109
	Combined by BIC	0.065	0.064	110	109
	Combined by EW	0.064	0.061	110	104
	AR(1)	0.059	0.059	100	100

*Parameter estimation rolling window starts at window Jan 1992-Dec1999.
AR (1) 1 step-ahead forecast.
Ratios over 100 show that the AR(1) forecasts outperform the MIDAS.
Univariate MIDAS monthly S&PGSCI return onto the lagged return and the Canadian dollar US terms.
Univariate MIDAS monthly S&PGSCI return onto the lagged return and the daily Baltic Dry Index.

Table 7

RMSE's 1-step ahead forecast (out-sample forecast), rolling window*

MIDAS models vs benchmark AR(1)

Periods	RMSE	Forecast Exp Almon	Forecast Beta	Forecast Exp Almon	Forecast Beta
	Model1 (AUD)	0.067	0.066	102	101
2000-2005	Model2 (3-Month tb)	0.067	0.066	102	101
	Combined by MSFE	0.066	0.066	101	101
	Combined by DMFSE	0.067	0.066	101	101
	Combined by AIC	0.067	0.066	102	101
	Combined by BIC	0.067	0.066	102	101
	Combined by EW	0.067	0.066	101	101
	AR(1)	0.066	0.066	100	100
2006-2009	Model1 (AUD)	0.083	0.085	104	107
	Model2 (3-Month tb)	0.089	0.084	112	106
	Combined by MSFE	0.085	0.084	107	106
	Combined by DMFSE	0.085	0.084	107	106
	Combined by AIC	0.083	0.084	104	106
	Combined by BIC	0.083	0.084	104	106
	Combined by EW	0.085	0.084	107	106
	AR(1)	0.079	0.079	100	100
2010-2016	Model1 (AUD)	0.061	0.062	104	105
	Model2 (3-Month tb)	0.063	0.061	107	104
	Combined by MSFE	0.062	0.061	105	104
	Combined by DMFSE	0.062	0.061	105	104
	Combined by AIC	0.061	0.061	104	104
	Combined by BIC	0.061	0.061	104	104
	Combined by EW	0.062	0.061	105	104
	AR(1)	0.059	0.059	100	100

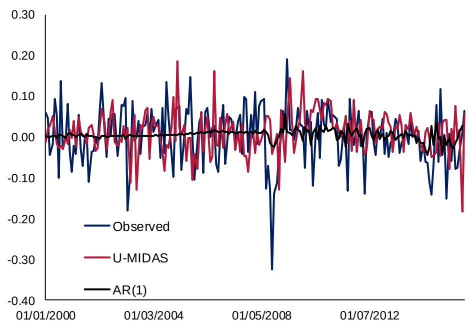
*Parameter estimation rolling window starts at window Jan1992-Dec1999.
AR(1) 1 step- ahead forecast.
Ratios over 100 show that the AR(1) forecasts outperform the MIDAS.
Univariate MIDAS monthly S&PGSCI return onto the lagged return and the Australian dollar US terms.
Univariate MIDAS monthly S&PGSCI return onto the lagged return and the daily 3- Month treasury bill.

My research, consistent with Chen, Roggo and Rossi (2010) found that commodity currencies can forecast commodity prices due to their exogeneous and forward-looking nature. My recursive MIDAS exercise shows that during the period of more financial uncertainty the Chilean peso also helps to predict an aggregated measure of commodity prices in this case the S&PGSCI by improving the accuracy of the univariate MIDAS forecasts. In addition to this the commodity forecasts displayed on Graphs 2a and 2b illustrate that commodity currencies along with the displayed financial variables tend to capture better-at least to some extent- the commodity price dynamics relative to the AR model.

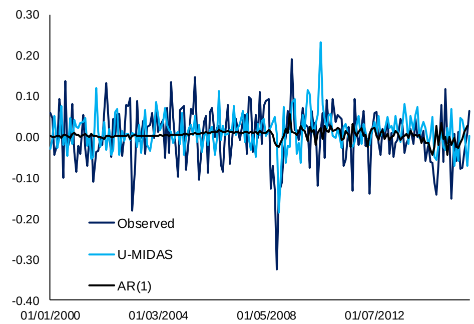
These results are also in line with Gargano and Timmerman (2014) who find commodity currencies carry some predictive power over the monthly horizon, and that commodity prices predictability is stronger during economic recessions.

Graph 2a

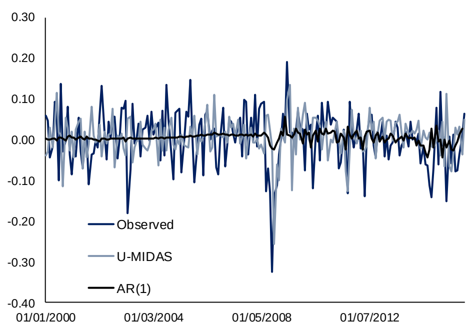
Monthly S&PSGCI return forecast (CAD) and AR(1)



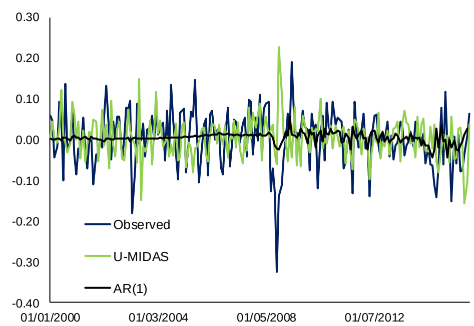
Monthly S&PSGCI return forecast MIDAS (AUD) and AR(1)



Monthly S&PSGCI return forecast (NZD) and AR(1)

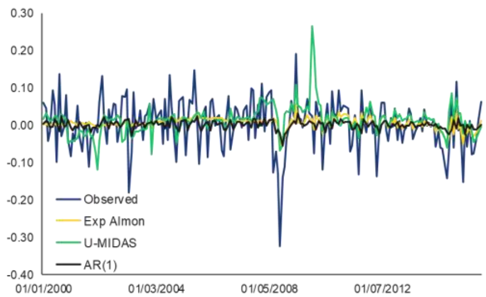


Monthly S&PSGCI return forecast MIDAS (ZAR) and AR(1)

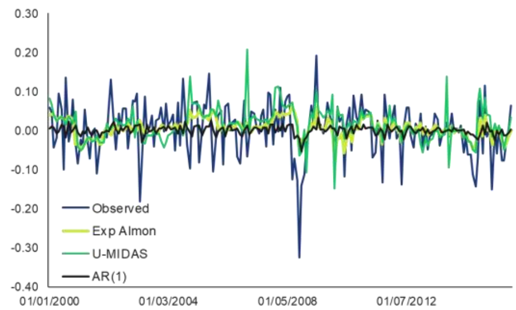


Graph 2b

Monthly S&PSGCI return forecast MIDAS (3-Month tb) AND AR(1)



Monthly S&PSGCI return forecast MIDAS (BDI) AND AR(1)



Source: own computations with data from Bloomberg

Furthermore, the evidence implies that financial and currency predictors by individual means do not offer systematically better forecasts than the autoregressive model AR(1).

1.5.2 Financialization of commodity markets: managed money spreading positions

Different studies also argue that the dynamic of commodity prices relies on different fundamentals such as economic growth, inventory and supply disruptions, monetary and exchange rates policies, along with the possible impact of speculation. Groen and Pesenti (2011).

Another of my objectives is to explore the role of speculation by measuring on the accuracy of the S&PGSCI monthly return forecasts using weekly managed money spreading positions of future agricultural markets: wheat, corn and soybeans in a MIDAS framework. To the best of my knowledge there are no exercises that evaluate the impact of managed money spread positions on commodity spot or futures prices in a mixed frequency data context for any aggregated or disaggregated commodity measures.

Some studies that explore the impact of speculation on commodity prices have been conducted. For instance, Hong and Yogo (2012) argue on their research that open interest conveys information about future expectations of economic activity and asset prices, and thus it is useful in predicting commodity prices and bond returns, open interest is being considered as a strong predictor to forecast inflation and economic growth. On a similar line, Singleton (2014) documented a study which evidences the importance of the index investors and managed money spreading positions as the main cause explaining the surge on oil futures prices during the crisis of 2008.

Inspired by Singleton (2014) and Hamilton and Wu (2015) findings I try to capture in a univariate MIDAS and monthly model specifications the possible effect that managed money spreading positions can carry on commodity prices predictability. As specified on section 5.4.1 and 5.4.2 the correspondent forecasting equations are described by equation 3 for the Mixed Data Sampling (MIDAS) forecasting model, and by equation 4 for the monthly model. The estimation of parameters is also done following a rolling window and recursive method. Given data constraint, my out of sample empirical experiment starts from 2006 and the forecasting estimation period begins at 2008. The included speculative positions are the ones reported at the agricultural futures market: wheat, corn, soybeans and my own weighted measure of grains.

The forecasting MIDAS equation includes the monthly lagged S&PGSCI return and the 12 lags of weekly speculative positions. The monthly model equation can or cannot include the one month lagged dependent variable but it considers the 3 lags of monthly managed money spreading positions. According to Singleton the rationale of this is explained by the fact that the effect of speculative activity is reflected on commodity prices with an almost three-month lag. This author evidence a strong predictive power of the 13-week-change of managed money spreading positions on the oil futures market.

As illustrated in Tables 8 and 9, the most interesting result of my empirical exercise is that during financial uncertainty there is some predictability of the S&PGSCI returns coming from the managed money spreading positions of the futures agricultural markets. My evidence suggests that during the crisis period Sep2009-Dec2010 the monthly model specifications which incorporate the speculative measures of agricultural managed money spreading positions of soybeans, corn and my grains measure improve the forecasting accuracy of the monthly models compared to the AR(1) benchmark.

A plausible explanation is that there is a relation between the index investors' behaviour trading with these agricultural commodities –which are included in the S&PGSCI- and the S&PGSCI, fact consistent with Tang and Xion (2011) whose findings show an increasing correlation between futures prices of non-energy commodities and the price of oil after 2004. Arguing that the index investor's behaviour should affect more commodities included in the S&PGSCI because portfolio allocation tends to trade in and out of commodities of an aggregated commodity index measure and other financial assets like bonds and stocks.

On the other side, it seems that during periods of relative economic stability 2011-2016 the MIDAS model specifications, following the rolling window method, tend to offer more accurate forecasts compared with the monthly models, but still the forecasts generated by the AR (1) models tend to be more efficient, despite the fact that wheat and grains speculative measures display similar forecasts to the autoregressive benchmark. For the post- crisis period only my measure of grains of speculative positions offers a RMSE reduction of 2 % for MIDAS models which include it relative to the AR(1) forecasts.

The forecasting evaluation of the whole period Sep2009-2016 does not show a clear improvement on forecasting accuracy of including any of the speculative measures in the MIDAS models compared to the AR (1) benchmark. It seems that the MIDAS models for the corn and soybeans outperform from 1 to 5 % the forecasts of the monthly models, nevertheless the AR (1) predictions tend to be similar or better except from the monthly model that incorporates the proxy of grains speculative positions.

Table 8

Speculative Positions

RMSE's 1-step ahead forecast (out-sample forecast), rolling window*

MIDAS models vs benchmarks AR(1) and monthly model

Periods	RMSE	Corn [1/]	Soybeans [1/]	Wheat [1/]	Grains [2/]	Corn vs		Soybeans vs		Wheat vs		Grains vs	
						AR(1)	Monthly	AR(1)	Monthly	AR(1)	Monthly	AR(1)	Monthly
	Beta	0.076	0.072	0.077	0.077	107	108	102	111	109	104	108	118
Sep2009-2010	Exp Almon	0.073	0.072	0.078	0.074	103	104	101	111	109	105	104	113
	Monthly model	0.070	0.065	0.074	0.065	99	100	91	100	104	100	92	100
	AR(1)	0.071	0.071	0.071	0.071	100		100		100		100	
	Beta	0.064	0.064	0.061	0.059	106	97	106	91	101	98	98	97
2011-2016	Exp Almon	0.061	0.066	0.060	0.062	102	93	110	95	100	98	104	102
	Monthly model	0.066	0.070	0.062	0.061	109	100	116	100	102	100	101	100
	AR(1)	0.060	0.060	0.060	0.060	100		100		100		100	
	Beta	0.066	0.065	0.064	0.063	106	99	105	95	103	100	101	102
Sep2009-2016	Exp Almon	0.063	0.067	0.063	0.064	102	95	108	98	102	99	104	105
	Monthly model	0.066	0.068	0.064	0.061	107	100	110	100	103	100	99	100
	AR(1)	0.062	0.062	0.062	0.062	100		100		100		100	

*Parameter estimation by rolling window starts at window Sep2006-Aug2009.
AR(1) 1 step- ahead forecast.
$y_{t+1} = \beta_0 + \beta_1 x_t + \beta_0 x_{t-1} + \beta_0 x_{t-2}$ as the monthly model
Ratios under 100 show that the MIDAS model outperform the AR(1) and monthly model.
[1/] Univariate MIDAS monthly S&PGSCI return onto lagged return and weekly log managed money spreading notional exposure of Corn, Soybeans and Soft Red Winter Wheat, respectively, of CBOT. (CFTC Disaggregated report futures only).
[2/] Grains corresponds to the own computation based on the S&PGSCI 2015 future contracts weights of the 2016 methodology.

Table 9

Speculative Positions

RMSE's 1-step ahead forecast (out-sample forecast), rolling window*

MIDAS models vs benchmarks AR(1) and monthly model

Periods	RMSE	Corn [1/]	Soybeans [1/]	Wheat [1/]	Grains [2/]	Corn vs		Soybeans vs		Wheat vs		Grains vs	
						AR(1)	Monthly	AR(1)	Monthly	AR(1)	Monthly	AR(1)	Monthly
	Beta	0.076	0.072	0.077	0.077	107	110	102	106	109	108	108	114
Sep2009-2010	Exp Almon	0.073	0.072	0.078	0.074	103	106	101	106	109	108	104	109
	Monthly model	0.069	0.068	0.072	0.067	97	100	96	100	101	100	95	100
	AR(1)	0.071	0.071	0.071	0.071	100		100		100		100	
	Beta	0.064	0.064	0.061	0.059	106	98	106	93	101	98	98	96
2011-2016	Exp Almon	0.061	0.066	0.060	0.062	102	94	110	96	100	97	104	101
	Monthly model	0.065	0.069	0.062	0.062	108	100	114	100	103	100	102	100
	AR(1)	0.060	0.060	0.060	0.060	100		100		100		100	
	Beta	0.066	0.065	0.064	0.063	106	101	105	95	103	100	101	100
Sep2009-2016	Exp Almon	0.063	0.067	0.063	0.064	102	97	108	98	102	100	104	103
	Monthly model	0.065	0.068	0.064	0.062	105	100	110	100	103	100	101	100
	AR(1)	0.062	0.062	0.062	0.062	100		100		100		100	

*Parameter estimation by rolling window starts at window Sep2006-Aug2009.
AR(1) 1 step- ahead forecast.
$y_{t+1} = \beta_0 + \mu y_t + \beta_1 x_t + \beta_0 x_{t-1} + \beta_0 x_{t-2}$ as the monthly model which also includes the first lag of the dependent variable.

Ratios under 100 show that the MIDAS model outperform the AR(1) and monthly model.
[1/] Univariate MIDAS monthly S&PGSCI return onto lagged return and weekly log managed money spreading notional exposure of Corn, Soybeans and Soft Red Winter Wheat, respectively, of CBOT. (CFTC Disaggregated report futures only).
[2/] Grains corresponds to the own computation based on the S&PGSCI 2015 future contracts weights of the 2016 methodology.

Nevertheless, the piece of evidence displayed in Table 10 shows that the monthly models estimated by a recursive window which include agricultural managed money positions can offer more accurate forecasts relative to the AR (1) for all periods. These results seem to be in favour of incorporating grains managed money positions into the regression forecasts. During economic uncertainty, the monthly models that incorporate corn, soybeans or wheat managed money spreading positions tend to improve the forecast in 4 and 3 % respectively compared to the AR (1) specifications.

For the forecasting evaluation period 2009-2016, the monthly models, estimated recursively by means of agricultural managed money spreading positions offer more accurate forecasts than the Autoregressive forecasts. Being more important when including the wheat positions, as the RMSE reduction can be up to 3 percent, whereas including my measure of grains or soybeans, speculative positions can improve in 2 and 1 percent respectively the predicting accuracy relative to the AR (1).

Table 10

Speculative Positions

RMSE's 1-step ahead forecast (out-sample forecast), recursive window*

MIDAS models vs benchmark AR(1)

Periods	RMSE	Corn [1/]	Soybeans [1/]	Wheat [1/]	Grains [2/]	Corn vs		Soybeans vs		Wheat vs		Grains vs	
						AR(1)	Monthly	AR(1)	Monthly	AR(1)	Monthly	AR(1)	Monthly
	Beta	0.073	0.070	0.072	0.071	106	110	103	107	105	109	104	108
Sep2009-2010	Exp Almon	0.070	0.071	0.073	0.070	103	107	104	108	106	110	103	107
	Monthly model	0.066	0.066	0.066	0.066	96	100	96	100	97	100	96	100
	AR(1)	0.068	0.068	0.068	0.068	100		100		100		100	
	Beta	0.060	0.061	0.060	0.061	100	101	101	101	100	103	101	103
2011-2016	Exp Almon	0.061	0.059	0.060	0.061	101	102	99	99	100	103	101	103
	Monthly model	0.060	0.060	0.058	0.059	99	100	100	100	97	100	98	100
	AR(1)	0.060	0.060	0.060	0.060	100		100		100		100	
	Beta	0.062	0.062	0.062	0.063	102	103	101	103	101	104	102	104
Sep2009-2016	Exp Almon	0.062	0.061	0.062	0.062	102	103	100	101	101	105	102	104
	Monthly model	0.061	0.061	0.060	0.060	99	100	99	100	97	100	98	100
	AR(1)	0.061	0.061	0.061	0.061	100		100		100		100	

*Parameter estimation by recursive window starts at window Sep 2006-Aug 2009.
AR(1) 1 step- ahead forecast.

$y_{t+1} = \beta_0 + \mu y_t + \beta_1 x_t + \beta_0 x_{t-1} + \beta_0 x_{t-2}$ as the monthly model which also includes the first lag of the dependent variable.
Ratios under 100 show that the MIDAS model outperform the AR(1)
1/ Univariate MIDAS monthly S&PGSCI return onto lagged return and weekly log managed money spreading notional exposure of Corn, Soybeans and Soft Red Winter Wheat, respectively, of CBOT. (CFTC Disaggregated report futures only).
2/ Grains corresponds to the own computation based on the S&PGSCI 2015 future contracts weights of the 2016 methodology.

Table 11

Speculative Positions

RMSE's 1-step ahead forecast (out-sample forecast), recursive window*

MIDAS models vs benchmark AR(1)

Periods	RMSE	Corn 1/	Soybeans 1/	Wheat 1/	Grains 2/	Corn vs AR(1)	Corn vs Monthly	Soybeans vs AR(1)	Soybeans vs Monthly	Wheat vs AR(1)	Wheat vs Monthly	Grains vs AR(1)	Grains vs Monthly
	Beta	0.072	0.071	0.069	0.071	106	110	104	108	101	105	104	108
Sep2009-2010	Exp Almon	0.070	0.070	0.068	0.071	102	106	102	106	100	104	103	108
	Monthly model	0.066	0.066	0.066	0.066	96	100	96	100	96	100	96	100
	AR(1)	0.068	0.068	0.068	0.068	100		100		100		100	
	Beta	0.061	0.060	0.060	0.061	102	103	100	101	100	101	101	102
2011-2016	Exp Almon	0.062	0.060	0.061	0.061	103	104	100	101	101	102	101	102
	Monthly model	0.060	0.060	0.060	0.060	99	100	99	100	99	100	99	100
	AR(1)	0.060	0.060	0.060	0.060	100		100		100		100	
	Beta	0.063	0.062	0.062	0.062	103	104	101	103	101	102	102	103
Sep2009-2016	Exp Almon	0.063	0.062	0.062	0.063	103	105	101	102	101	102	102	103
	Monthly model	0.061	0.061	0.060	0.061	99	100	99	100	98	100	99	100
	AR(1)	0.061	0.061	0.061	0.061	100		100		100		100	

*Parameter estimation by recursive window starts at window Sep 2006-Aug 2009.
AR(1) 1 step- ahead forecast.
$y_{t+1} = \beta_0 + \mu y_t + \beta_1 x_t + \beta_0 x_{t-1} + \beta_0 x_{t-2}$ as the monthly model which also includes the first lag of the dependent variable.
Ratios under 100 show that the MIDAS model outperform the AR(1)
1/ Univariate MIDAS monthly S&PGSCI return onto lagged return and weekly log open interest notional exposure of Corn, Soybeans and Soft Red Winter Wheat, respectively, of CBOT. (CFTC Disaggregated report futures only).
2/ Grains corresponds to the own computation based on the S&PGSCI 2015 future contracts weights of the 2016 methodology.

Results displayed on Table 11 confirm that speculation helps to improve the forecasting accuracy of a popular benchmark when forecasting the monthly log returns of S&PGSCI, since the RSME reductions are similar when the used regressor is Open Interest instead of Managed Money Positions. Similar to the previous Table, the RSME register the bigger reductions during the period that includes the financial crisis (Sep2009-2010) with 4 % for the four grain measures. And the preferable forecast comes from the monthly specification over the AR (1) and the MIDAS regressions.

In contrast to some findings such as Hamilton and Wu (2015), where the speculative positions measured with the log index-investor's notional exposure of the 12 agricultural commodities evaluated do not show predictive power, my evidence seems to be more in line with more agnostic findings such as the ones of Singleton (2014), Hong and Yogo (2013) and Gargano and Timmerman (2014). The latter found consistent predictability of the open interest over commodity prices across different forecasting horizons, and that predictability was stronger during economic recessions.

The convenience yield and storage costs are contained in financial and macroeconomic variables which can drive commodity prices. However, Singleton's (2014) arguments seem to make sense in explaining the improvements in forecasting accuracy when using managed money positions overall during periods of economic uncertainty. As he argues the speculative positions may impact futures prices by affecting the risk premium or informational channels due to the heterogenous interpretation about public available information even among the same category of investors which ultimately will affect the way investors move their funds into commodity markets.

Consistent with Singleton (2014) and Hong and Yogo (2012) my evidence may indicate that given limited arbitrage by speculators, and their different interpretation of the market fundamentals, changes in open interest are a more solid forward-looking measure of economic activity and asset prices by affecting risk premiums (through asset allocation in concordance with their disagreement over public imperfect information) and ultimately impact commodity futures prices in a unique direction. In concordance with the agnostic approach open interest and thus managed money spreading positions increments utterly embedded information relative to a higher economic activity and therefore by impacting risk premiums, higher funds coming from speculative investors' impact commodity futures prices in a positive manner. Conversely, futures prices themselves send opposite signals to market participants since futures prices may rise or fall as a response of a higher economic activity perception precisely due to the limited risk capacity in the futures markets.

1.6 Conclusion

The results suggest that the MIDAS model specifications which offer more efficient commodity monthly return forecasts relative to the autoregressive model are those whose parameters are estimated recursively. This holds true for the univariate MIDAS models that incorporate financial variables, commodity currencies and speculative positions as predictors. My results are consistent with that conclusion especially during a crisis period, speculative positions embodied known relative information by speculative investors who interpret the economy heterogeneously about the future state of the economy and therefore help in predicting an aggregated measure of commodity prices. The Chilean peso also helps to get more accurate commodity price forecasts.

Putting this into perspective, why was it sensible to link investor behaviour as one of the drivers of S&P Goldman Sach index? The S&P Goldman and Sachs has been considered as global measured of spot prices; however, the nature of its composition includes liquid contracts from futures markets, which in principle to me suggests that their changes are more likely to be driven by the futures markets rather than the spot ones. The nature of the index is constructed by the rolling strategy of futures contracts, where the energy sector accounts for 63.0% and the grains sector for 11.6% according to the 2016 Methodology. Thus, it makes sense to associate the dynamic of this commodity index to the dynamics of the futures markets: what determines the oil futures markets and agricultural market dynamics should also influence this global measure of commodity prices.

My forecasting combining exercise show that in none of the cases the MIDAS models or their combinations by means of financial variables and commodity currencies, whose models where estimated by a rolling window method, are more efficient than the AR(1) benchmark forecasts. Relative to the MIDAS individual models there is almost imperceptible gain of combining the BDI and the Cad MIDAS forecasts compared to the MIDAS specifications that only incorporate the BDI.

Despite the fact that there are no clear signals that the MIDAS specifications offer systematically more accurate commodity return predictions compared to the autoregressive model, which is line with previous findings on the literature, see for instance Baumeister, Guérin, and Kilian (2014), and Etienne (2015). The improvement in forecasting accuracy by means of speculative positions, overall during periods of economic instability may indicate, as argued by Singleton, that these speculative positions contain more valuable information about the heterogeneous investors' beliefs over the future state of the economy and may reflect more accurately or with more opportunity this knowledge than past commodity prices. Yet there is no consensus in the literature about what has been driving commodity prices lately if fundamentals or speculative behaviour.

Chapter 2

2. Forecasting the Realised Volatility of Global Commodity Returns

2.1 Introduction

Much of the volatility literature has been devoted to understanding the sources of volatility of financial indices rather than volatility forecasting. The majority of studies have been focused on the dynamics in the stock markets. And therefore, not much has been said regarding volatility on the commodity markets. Despite this there are some chapters that have studied the volatility dynamics in the agricultural and energetic markets, very few have focused on explaining and forecasting the market volatility measured from of one of the global commodity benchmarks: the Bloomberg Commodity Index Excess return (BCOM).

The relevance of commodity indexes is well explained by Fong, W.M. and Kim, H.S. (2001) who state that commodity index futures are a powerful tool for investors to gain exposure to commodity markets, to diversify from traditional financial assets as stock and bonds markets. Offering a hedging option with respect financial assets and inflation, because of the negative correlation among them and commodity returns. Thus, they shed some light on the time series dynamics of the conditional volatility of commodity returns which is also important for options and futures markets pricing.

Regarding volatility forecasting there is a more recent paper where the aim is to predict the monthly return market volatility (constructed from daily returns) of equities, foreign exchange, bonds and commodities (S&PGSCI) and it involves variable selection from a subset of macroeconomic and financial variables within a Bayesian Approach. (See Christiansen, Schmeling, and Schrimpf, 2012). One of the most recent papers on global market volatility is presented by Smales (2017) which studies the impact of macroeconomic news of US and China on the global commodity volatility measure by the commodity benchmark (S&PGSCI).

Consequently, trying to contribute to the literature on volatility forecasting for the global commodity markets. Using RMSE metrics I test the forecasting accuracy of competing models by forecasting range-price estimators as a proxy of daily realised volatility of global commodity returns of three different measures of realised volatility under the Heteregoeneous Autoregressesive (HAR) approach[20] , using data from the Bloomberg Commodity Index Excess return obtained from Bloomberg.

Following Viteva, Veld-Merkoulova, and Campbell (2014) who state that in absence of high frequency data, the next proxies of realised volatility are absolute returns and two range-price estimators are alternatives to the popular realised volatility measures of Andersen and Bollerslev, which optimal sampling prices range varies from 5 to 30 minutes to even 1 hour. Furthermore Patton (2011) also states that an alternative to daily squared returns and the realised volatility measure is the range-price estimator of Parkinson, these two proxies are more efficient and unbiased estimators of the conditional volatility than the daily squared return.

Regarding sensible predictors to forecast market volatility, literature has reported the predictive power of the Implied volatility (VIX)[21] in forecasting future realised stock market volatility which has been superior to standard Models (GARCH). Given this evidence for the equity markets, it is then natural to try to test if there is useful information contained in an implied volatility measure for the commodity markets. In this case the implied volatility measure for at the money call options of the Dow Jones-UBS Commodity Index whose underlying is the Bloomberg Commodity Index Excess Return.

The study is organized in five sections. The first section describes previous findings in the literature regarding realised volatility forecasting, subdivided into three parts

[20] The HAR model allows us to approximate the long memory property of the realised volatility by the use of lagged heterogeneous autoregressive process (see Corsi, 2009).

[21] According to the Chicago Board Options Exchange (CBOE), since 2003, the VIX measures the market's expectation of the 30-day volatility implied by averaging the weighted prices of S&P500 puts and calls options over a wide range of strike prices, including from 2014 the S&P500 weekly options. In 1993, at the beginning the VIX measured the expected volatility of at- the-money option prices of the S&P100.

which discuss the financial literature relative to modelling and forecasting volatility in financial markets, and volatility: latent conditional volatility and realised volatility, the last part considers speculation and commodity price volatility.

The second section describes the data that is used to estimate the models that forecasts the realised volatility of the Bloomberg Commodity Index Excess Return (BCOM), and it also explains the rationale of the alternative three measures of realised volatility to end with general data descriptive statistics, including the log returns and the realised volatility measures which suggest that the volatility process is a persistent process which is non-normal distributed in concordance with previous findings. Section three describes the Methodology based on the stylized facts of volatility. Hence the Heterogenous Autoregressive model captures well the persistence in the volatility process along with some non-normal features.

Section four discusses about the empirical analysis which is subdivided into two subsections. The first subsection describes the in-sample results which show that the implied volatility measure is a biased estimator of the future realised volatility of the commodity markets, also denoting that the HAR and HAR-IV specifications are preferred over the alternative models due to the higher R^2. The second subsection examines the forecasting accuracy of the contending models relative to the benchmarks GARCH (1,1) and E-GARCH (1,1), showing that the HAR and HAR-IV are offer better forecasts that are statistically significant relative to the alternatives. The fifth and final section explains the main conclusions.

2.2. Literature Review

2.2.1 Modelling and Forecasting Volatility in Financial Markets

It is well known that the joint Distributional characteristics of asset returns are crucial in determining prices of financial instruments and related to the risk-return trade-off that is important for portfolio allocation and also relevant to financial risk management. Special interest has been focused on the structure of the time -varying variance which ultimately has resulted in a rich literature about modelling and forecasting return volatility. Inclusion of high-frequency data has helped to improve the forecast performance, because high-frequency volatility is highly predictable, and this data also carries useful information to forecast lower-frequency horizons (See Andersen, Bollerslev, Diebold, and Labys, 2003).

2.2.2 Modelling and Forecasting Realised Measures of Volatility

2.2.2.1 Modelling and Forecasting Volatility for stock market and exchange rates

A study that formally links the realised volatility and conditional variance of foreign exchange returns is the one presented by Andersen, Bollerslev, Diebold, and Labys (2003). They base their framework on the theory of continuous-time no-arbitrage processes and the theory of quadratic variation[22] so that they can model and forecast the daily realised volatility (the quadratic return variation) using simple models based on the observed variables -this can be achieved by the fact they treat volatility as observed instead of latent-, using continuously recorded Deutschemark and Yen spot exchange rates, both in dollar terms from 1986 to 1999.

Their study evidences that superior forecasts for the logarithmic daily realised volatilities of the aforementioned exchange rates can be generated by long-memory Gaussian vector autoregressive models (simple Gaussian VAR) compared to the forecasts obtained with popular daily volatility models (including the GARCH (1,1) model) and high-frequency models (high-frequency FIEGARCH, that incorporates a long memory component). In addition, under the assumption of normally distributed returns conditional on the realised volatilities based on theoretical background, a

[22] For a more detail explanation of the theoretical background, see Andersen, Bollerslev, Diebold, and Labys, 2003.

parametric lognormal-normal mixture forecast distribution also estimates accurate density forecasts and quantile predictions of future returns.

Hansen and Lunde (2011) categorize in two the type of models available to forecast the realised volatility: reduced form volatility and model-based volatility forecasts. The reduced form volatility forecasts allow the researcher to capture the persistence of the volatility with methods that resemble the simple exponential smoothing forecast. These models include the distributed lag models and the extension of Mixed Data Sampling (MIDAS) models, the ARFIMA -they come from the long-memory Gaussian VAR of Andersen, Bollerslev, Diebold, and Labys (2003)-, and the Heterogenous Autoregressive Model of Realised Variance (HAR) that has proved to be successful.

In the MIDAS framework, Ghysels, Synko and Valkanov (2007) discuss about different volatility measures and offer some empirical evidence of the impact of microstructure noise[23] on volatility prediction on asset prices, when modelling volatility an accounting for its persistence. They use intra-day volatility measures of quadratic variation (the RV 5-min) adjusted and unadjusted by microstructure noise, following Hansen and Lunde (2005), as a measure of the daily variance.

Their empirical results show that correcting by microstructure noise improves the forecast of futured corrected increments for Alcoa Inc (AA). and Microsoft stocks. For the both stocks the unadjusted RV 5-min (realised variance based on absolute returns constructed using intraday data) has the best explanatory power across models and all samples, except for the full sample for the Microsoft stock.

Ghysels, Synko and Valkanov (2007) also suggest the use of non-linear MIDAS specifications in a parameter dependent function to test for leverage and box-cox transformation and also discuss the appealing of multivariate MIDAS when testing for Granger-Causality. To test for leverage-effect one can try to predict the future log volatility of returns in a similar fashion to the E-GARCH models, and by the use of

[23] The microstructure noise can come from three main sources: price discreteness issues, asymmetric information and bid-ask spreads (See Ghysels, Synko and Valkanov, 2007).

multivariate MIDAS models one can have analogous models to the ARCH- in- mean specifications. In the multivariate case, the MIDAS models could help in testing Granger- causality by alleviating some of the problems relative to the temporal aggregation of predictor variables.

The model-based volatility forecasts of Hansen and Lunde (2011) include the GARCH models with the inclusion of realised measures of volatility. The conditional variance of realised measures of volatility differs from the conditional variance as a function of past returns, and the difference is higher after a sudden change in the conditional variance. In this context, the standard GARCH methodology is modified to consider realised measures of volatilities. Such as the GARCHX, that includes past values of a realised measure of volatility as an exogenous variable that is part of the conditional variance equation. Some literature has evidenced that including the realised variance or bi-power variation to estimate the conditional variance has wiped out the significance of the squared returns (See Engel,2002, and Barndorff-Nielsen and Shephard, 2010 in Hansen and Lunde, 2011).

Further extensions of these models are the Heavy Models of Shephard, and Sheppard (2010) and the Realised GARCH model presented by Hansen, Huang, and Shek (2012) which is used to estimate the latent conditional volatility and returns of the stock market, as a function of their past values and a realised measure of volatility and a leverage function. In their study they found for the Dow Jones Industrial Average stocks and an exchange traded index fund that a simple log-linear Realised GARCH model improves the fit compared to the standard GARCH models that just use daily returns, finding the leverage function as highly significant.

The realised GARCH with linear or log-linear specifications models returns and the realised volatility, by the use of a measurement equation[24] which estimates in a simple fashion the dependence between returns and future volatility, thus linking the realised volatility with the conditional variance of returns, by the presence of a

[24] The Measurement equation is a function of the realised measure of volatility on the past conditional variance -which is a function of past values of conditional variance and past values of a realised measure of volatility, a leverage function -that models the joint dependence between the realised volatility and returns -., and an error term (For more detail see Hansen, Huang and Shek, 2012).

leverage function in the measurement equation. The inclusion of a measurement equation links the realised measured to the latent conditional variance.

The Realised GARCH models the latent conditional variance -similarly to the standard GARCH model-, as a function of its own lag values and lagged squared returns values, but in the Realised GARCH the conditional variance it is also a function of lagged values of a realised measure of volatility such as: realised variance, bi-power variation and the realised kernel, which contain more information of the actual level of volatility than the daily squared returns used in standard GARCH models. (See Hansen, Huang and Shek, 2012).

Other studies that account for more stylized facts of asset returns is the one presented by Chen, and Ghysels (2011), which accounts not only for the volatility persistence but as well for the impact of information asymmetries that translate as the negative correlation between equity returns and volatility, which can be due to a leverage effect or a volatility feed-back effect. The first one can affect the conditional volatility, and the second one is the effect of volatility on time-varying risk premia. Volatility prediction models that use realised measures of volatility involve linear regressions and lagged realised volatility corrected for jumps or microstructure noise.

Chen and Ghysels (2011) highlight the importance of accounting for information asymmetries, by the use of semi-parametric MIDAS models, to allow for a non-parametric specification of the news impact curve, and parametric models applied to intra-day returns based on asymmetric daily GARCH models (E-GARCH).

2.2.2.2 Modelling and Forecasting Volatility in Commodity Markets

2.2.2.2.1 Modelling Latent Conditional Volatility

One of the studies that models the conditional variance of futures returns of commodity index futures is provided by Fong, W.M. and Kim, H.S. (2001), they use data from the S&PGSCI to construct daily futures returns from 1992 to 1997, following a general Markov switching model that allows for abrupt changes or regime shifts (structural breaks) in volatility and mean, basis driven transition probabilities, GARCH dynamics and conditional heavier tails in the distribution of returns.

Fong, W.M. and Kim, H.S. (2001) show evidence in favour of the regime switching model to describe volatility dynamics better than single-regime GARCH models, hence, providing supporting evidence of regime shifts in conditional mean and volatility. Another relevant finding, consistent with the theory of storage, explains that the probability of remaining in a low volatility state or switching to a more volatile state depends on the basis, if this basis is positive it is more likely to remain in a low volatility environment, but if it is negative it is more likely to change to a more volatile one.

Musunuru, Yu, and Larson (2013) model and forecast volatility (understanding volatility as the change in the standard deviation of daily returns) of returns for corn futures prices[25] using GARCH models, to assess the asymmetries and the time-varying volatility of corn returns they use the T-GARCH and E-GARCH. They compare the forecasting accuracy of the GARCH models with the root mean square error, the mean absolute error, the mean absolute percent error and the Theil inequality coefficient. Their results show that the E-GARCH offers the best out-of-sample forecast among the models. Their other finding reveals a leverage effect on corn futures since the impact on volatility of bad news results being bigger than the one of good news.

These authors explain that understanding volatility can help market participants in selecting the investment portfolio and can be used as a tool to hedge against sharp price fluctuations. It can also be useful to minimize the market exposure of the corn farmers overall during periods of high uncertainty. Higher volatility can ultimately impact the stability of financial markets and economies by affecting beliefs among investors and increasing the risk of losses (See Pan and Zhang, 2006).

[25] The authors used a continuous corn futures contract from the settlement prices of the Chicago Board of Trade (CBTO) from January 1995 to June 2012.

2.2.2.2.2 Modelling and Forecasting Realised Volatility

Considering that realised measures of volatility contain valuable information regarding the latent conditional volatility, as previously discussed. It is natural to explore the use of these observed measures of volatility to estimate the volatility of commodity markets. For example, Huang, Huang and Matei (2012) analyse the role of high-frequency data following the Realised GARCH methodology of Hansen, Huang and Shek (2012) to forecast the volatility of four agricultural futures prices traded in U.S.A. The realised GARCH helps with the microstructure noise that affects the realised measures of volatility. In their study they present three different measures of realised volatility: 1-min Realised Variance, 5-min Realised Variance and the Realised Kernel.

In contrast with the original Gaussian Realised GARCH, by the inclusion of a standard student-t, they account for other distributional features of agricultural commodities return in the futures markets: skewness and fat tails. Comparing the forecasting performance of the Realised GARCH with the traditional GARCH and E-GARCH. To compare the in sample and out-of-sample fitting and forecasting they use the partial likelihoods.

Christiansen, Schmeling, and Schrimpf (2012) present a study on predicting monthly return market volatility of equities, foreign exchange, bonds and commodities by means of macroeconomic and financial variables. Following a Bayesian model averaging approach, model selection and forecast combination to determine which variables carry predictive power in predicting financial volatility for the measures of market volatilities. Their main findings show that economic variables are relevant in predicting market volatility for the equity, foreign exchange, bonds and commodity markets, and it is robust to including lagged volatility. In particular variables that are measures leverage, credit risk and funding illiquidity along with the ones that consider time-varying risk premia seem to appear as the economic drivers of financial volatility.

They use a realised volatility measure constructed from squared returns based on daily returns on the S&P 500 for the stock market measure, the realised bond market volatility is generated from returns on the 10-year Treasury note futures contract traded on the Chicago Board of Trade (CBOT), and for the commodity market volatility they use data from the S&PGSCI commodity index. For the foreign exchange market volatility they equally weighted a basket of foreign currencies to then being able to construct the realised market volatility measure for the foreign exchange market as in the case of the aforementioned financial assets. The time span for the monthly observations of US Equity market is from 1926 to 2010, and for the rest of the assets from 1983 to 2010.

Fengping, Ke and Langnan (2017) developed a new time-varying Realised Volatility (RV)[26] Heterogenous Autoregressive (HAR) model, to account for heterogeneous volatility components, and that incorporates all potential predictors, the model also includes the independent normal-gamma autoregressive (NGAR) process to control the sparsity of the posterior distribution of the regression coefficients and this NGAR also assumes that the predictors are more or less constant in the model.

The corresponding HAR allows the predictors and coefficient estimates to vary simultaneously to forecast the realised volatility (RV)[27] in the Chinese agricultural futures markets. They compare the forecasting accuracy of the model with other HAR-types by using the Model Confident Set (MCS). Fengping, Ke and Langnan (2017) evidence portray that their proposed model outperforms the competing models and their results are robust to different volatility measures.

2.2.3 Speculation and Commodity prices volatility

Regarding the role of speculation affecting short oil prices volatility, Beidas-Strom, and Pescatori (2014) understanding that speculation is reflected on oil inventories (inventory demand) given the high co-movement of these and oil prices, following the fundamentalist framework (Kilian 2009 and Kilian and Murphy 2013). Therefore,

---

[26] Fengping T., Ke Y., Langnan Ch. (2017) estimate the realised volatility as the sum of squared intraday returns.

[27] Fengping T., Ke Y., Langnan Ch. (2017) estimate the realised volatility as the sum of squared intraday returns.

by the use of a storage model described by structural Vector Autoregression Models (SVAR) they quantify the speculative effect (short-trading shocks) on short-oil price volatility when imposing some restrictions on the time horizon. Their findings show that the temporary impact of speculation on short oil prices volatility is lower than the one of the flow demand (current demand) but bigger than the supply shock.

2.3 Data

The empirical analysis is based on the daily raw data of the Bloomberg Commodity Index Excess Return (BCOM) (formerly Dow Jones-UBS) in US dollars[28] which is a benchmark for investments in commodity markets and was designed to be a highly liquid and diversified broad-based commodity index. This index computed on an excess return basis represents the price levels of designated and regulated futures contracts of 24 commodities including grains (23.46%), livestock (6.07%), softs (7.22%), industrial metals (17.39%), precious metals (15.29%) and energy (30.57%) prices, according to the Bloomberg Commodity Index Family Bloomberg Methodology (2017). To capture economic importance of the diverse commodities, liquidity and US-dollar weighted production is taking into account to assign weights to each commodity that conforms the BCOM.

Table 1 displays the availability of the Bloomberg Commodity Index Excess Return and the implied volatility of the Dow Jones-UBS Commodity Index

[28] "… This Methodology, the Information and the Index were acquired by UBS in May 2009 and remain UBS's exclusive property. This Methodology is the successor document to the Dow Jones-UBS Commodity Index Handbook published in prior years and replaces it in its entirety…" The Bloomberg Commodity Index Methodology, Bloomberg (2017, p.2)

Table 1

Commodity	Variables	Frequency	Start Date
Dow Jones-UBS Commodity Index	Implied Volatility Call	daily	27/06/2011
	Implied Volatility Put	daily	27/06/2011
Underlying:Bloomberg-Commodity Index Excess Return	Price Index	daily	01/02/1991

Source: Datastream and Bloomberg

Empirical evidence has shown that a realised measure is a useful predictor of volatility. For instance, according to the theory of quadratic variation, the realised volatility of Andersen and Bollerslev is an unbiased efficient estimator of volatility return that captures relevant intra-day information. For instance, the logarithmic realised volatility distribution of two foreign exchange rates behaves approximately as Gaussian. (See Andersen, Bollerslev, Diebold, and Labys, 2003).

Andersen and Bollerslev have acknowledged the fact that return variance is latent and put emphasis on the importance of having an accurate volatility proxy in order to model and forecast volatility (as cited in Hansen and Lunde, 2011) the realised volatility is a good volatility proxy because it is consistent with the integrated volatility, which is the return variance for the population, this consistency is achieved by sampling prices in a short enough interval of time. Optimal sampling frequencies ranges from 5 to 30 minutes to even 1 hour (For further information see Andersen, Bollerslev, Christoffersen and Diebold 2006).

Thus, given limited data availability, the main idea is to estimate alternative proxies to the popular aforementioned realised volatility measures following Viteva, Veld-Merkoulova, and Campbell (2014) which are absolute returns and two range-price estimators (Parkinson’s and Roger’s and Satchell’s) of the Bloomberg Commodity

Index Excess return in order to forecast the one-period ahead daily realised volatility following the Heterogeneous Autoregressive Methodology that includes the daily, weekly and monthly components of the realised volatility as predictors into the realised volatility equation.

In order to address the second question of this study, the implied volatility measure of the stock market S&P500, the VIX in US dollars from Bloomberg, and the implied volatility of the at the money call options of the Dow Jones -UBS Commodity Index in US dollars published by datastream (whose underlying is the Bloomberg Commodity Index Excess Return) are the other two predictors that will be included in the forecasting equation to see if they improve the forecasting accuracy of the daily realised variance for the commodity markets. Given data constraints, the implied volatility measures of the VIX and of the at the money call options of the Dow Jones-UBS Commodity Index are considered from June 27, 2011 to October 31, 2017.

The aforementioned realised volatility estimators are constructed from June 27, 2011 to October 31, 2017. These daily measures of realised volatility of the Bloomberg Commodity Index Excess return are based on the realised variance formulas used by Vietva, Merkoulova and Campbell (2014). Apart from the popular squared returns as a measure of realised volatility, I computed two extreme value volatility measures (range-based estimators) that have been proven useful to capture volatility dynamics of asset prices when higher-frequency data is not available. In the case of the present study these two measures: Parkinson´s (1980) and Rogers and Satchell´s (1991) will be computed from the raw daily data of the Bloomberg Commodity Excess Return. Parkinson´s (1980) measures includes the high/low prices of a day and Rogers and Satchell´s also incorporates the opening and closing prices to account for jumps during non-trading periods during a day. Due to availability of the data the daily log return is defined as the close-to-close return.

Daily log return (close to close)

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$$

Annualized Daily Realised Volatility measure with Daily Squared Returns[29]

$$\sigma_t = \sqrt{252 * R_t^2}$$

Where R_t^2 is the squared return computed with close to close interday prices.

Parkinson´s (1980)

$$\sigma_t{}^2 = \frac{1}{4\,ln2}[\ln(high_t) - \ln(low_t)]^2$$

Rogers and Satchell´s (1991)

$$\sigma_t{}^2 = \ln\left(\frac{high_t}{open_t}\right)\ln\left(\frac{high_t}{close_t}\right) + \ln\left(\frac{low_t}{open_t}\right)\ln\left(\frac{low_t}{close_t}\right)$$

Intra-day prices: high, low, open and close. All the volatility measures are annualized following conventions. The annualized daily volatilities of the Parkinson´s and Rogers and Satchell´s calculating the next formula:

$$\sigma_t = \sqrt{252} * \sqrt{\sigma_{t,i}^2}$$

Where *i=1 for the case of Parkinson's and 2 for Rogers and Satchell*

2.3.1 Data Descriptive Statistics

Table 2 displays the descriptive statistics of the log returns and Realised Variance Measures of the Bloomberg Commodity Excess Return Index and the Dow Jones-UBS Commodity Implied volatility of the money calls over the period July 28, 2011 to October 31, 2017.

Table 2 Descriptive Statistics of the log returns and realised volatility measures of the Bloomberg Commodity Excess Return and its implied volatility at daily frequency

[29] Since we are taking the square root of the daily squared return that equals to the daily absolute return.

		Realized Volatility				
	Log returns	Squared returns	Parkinson	Rogers	Implied volatility DJ-UBS Commodity	Implied volatility stock market (VIX)
Mean	-0.0004110	0.1002420	0.0891160	0.0823930	0.1454510	0.1628110
Median	-0.0001380	0.0792380	0.0795100	0.0741330	0.1466000	0.1454000
Maximum	0.0370210	0.7154940	0.3434920	0.3751850	0.6744000	0.4800000
Minimum	-0.0450720	0.0000476	0.0036740	0.0000000	0.0018000	0.0919000
Std. Dev.	0.0083500	0.0869410	0.0457190	0.0459230	0.0521840	0.0577750
Skewness	-0.2074090	1.7730320	1.3026100	1.3017850	2.5197860	2.1214480
Kurtosis	4.7435040	8.0014710	5.7171290	6.0822870	25.3999800	8.2201380
Jarque-Bera	211.3149	2473.061	932.2652	1071.027	34682.5	2973.434
Probability	0	0	0	0	0	0
Sum	-0.649591	158.2826	140.7147	130.0988	229.6674	256.7535
Sum Sq. Dev.	0.110028	11.92775	3.298317	3.327887	4.297163	5.260592
Observations	1579	1579	1579	1579	1579	1577

Source: Own computations based on Bloomberg and Datastream data

As illustrated by Table 2, the continuously compounded daily return evidences an excess kurtosis above 4.5, and a slightly negative skewness, then commodity returns do not behave normally distributed, evidence consistent with findings of financial literature which show that financial returns do not behave normally distributed (See for example Corsi, 2009).

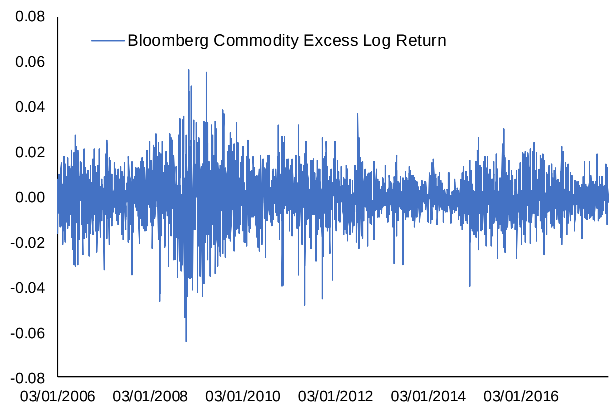
In the case of the daily Realised Volatilities measured by Roger´s, Parkinson´s formulas and squared returns, the kurtosis values are also positive, overall the daily squared return 8.00, followed by Rogers´s 6.08, and Parkinson´s 5.71, evidencing the presence of very fat tails, and positive skewness of 1.77, 1.30 and 1.30 for each of the three daily Realised Volatility measures, which indicates that each of the proxies of the Realised Volatility measures of commodities is not normally distributed and it shows higher risk of extreme values than the log returns.

The implied volatility of the DJ-UBS commodity and the implied volatility index of the stock market VIX, also exhibit positive kurtosis, overall the implied volatility of the commodity index with 25.39, and the VIX 8.22. Both implied volatility measures also show positive skewness of 2.51 and 2.12 respectively.

On the other hand, looking at the autocorrelation function of one of the Realised Volatility proxies. For instance, the non-parametric estimator of Roger's, it shows the persistence of the volatility in the commodity markets, thus portraying it as a long-memory process. As illustrated by Graph 2 and 3. Similar results are obtained for the two alternative volatility measures.

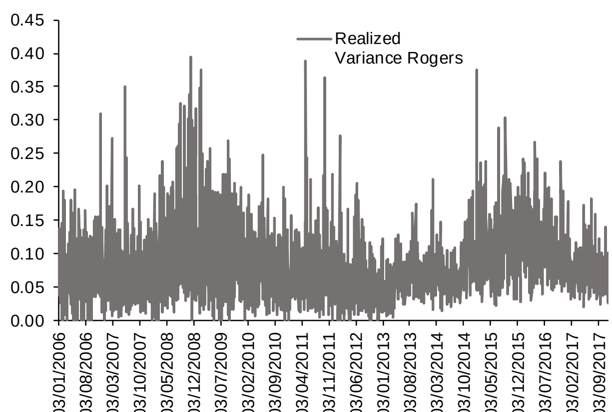
Bloomberg Commodity Excess Return: Log Returns

Graph 1



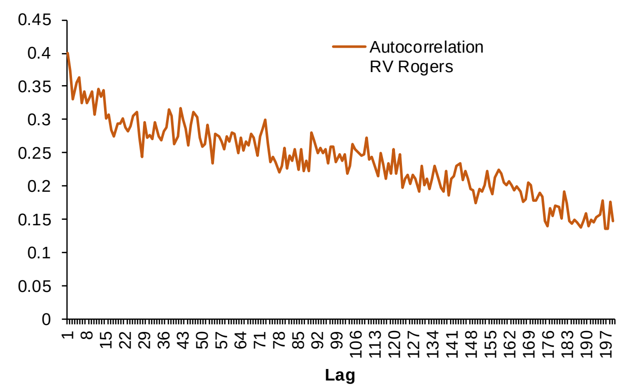
Graph 2

Realised Volatility Rogers



Graph 3

Autocorrelation Function of The Realised Volatility



Source: own computations with Bloomberg data.

2.4 Methodology: Heterogeneous Autoregressive Model (HAR), Implied Volatility and GARCH, EGARCH Models.

Considering that the purpose of this document is to contribute to the forecasting literature of Realised Volatility of global commodity prices, I follow the financial literature by taking into account the stylized facts of the daily Realised Volatility of the Bloomberg Commodity Index Excess Return described in Section 2: fat-tails, and the persistence in memory of the process.

And hence, the Heterogeneous Autoregressive Model (HAR) introduced by Corsi in 2009 is a parsimonious model that captures these aforementioned volatility features, by regressing (using OLS) the daily realised volatility as a function of the previous daily realised volatility, which is similar to the AR (1) component, and as a function of the weekly and monthly realised volatilities, based on the extensive literature regarding volatility propagation, where longer-term volatilities impact the shorter-term volatilities.

The Heterogeneous Autoregressive (HAR) Model

$$RV_{t+1\,d}{}^{(d)} = \beta_0 + \beta_1{}^{(d)} RV_t{}^{(d)} + \beta_2{}^{(w)} RV_t{}^{(w)} + \beta_3{}^{(m)} RV_t{}^{(m)} + \varepsilon_{t+1d} \quad (1)$$

For *t*=1, …,T; where $RV_{t+1\,d}{}^{(d)}$ is the daily Realised Volatility at the period $t+1$

the $RV_t{}^{(d)}$ is the daily Realised Volatility at period t,

the $RV_t{}^{(w)}$ is the weekly Realised Volatility component at period t

the $RV_t{}^{(m)}$ is the monthly Realised Volatility component at period t

the ε_{t+1d} is the disturbance term at period t [30]

the $\boldsymbol{\beta}$ is the column vector of coefficients associated to each of the Realised Volatility regressors that also includes the constant term.

[30] In order to ensure positiveness of the realised volatility measure Corsi (2009, p.180) explains that "…the volatility innovation ε_{t+1d} comes from contemporaneously and serially independent zero-mean nuisance variates with an appropriate truncated left tail…". Alternatively, the HAR model can be expressed in term of log realised volatilities.

The daily, weekly and monthly components are computed the following way

$$RV_{t+1}{}^{(h)} = \frac{1}{n}\sum_{i=1}^{n} RV_{t+1-i}{}^{(d)}$$

Where (h) can be (d) for daily, (w) for weekly and (m) for monthly.

n, takes the value of 1 for the daily component, 5 for the weekly component and 22 for the monthly component.

The HAR model describes well the long memory of the volatility process and it can help to contribute of the forecasting literature of Realised Volatility of a global measure of Commodity Prices: BCOM. This HAR model is the Benchmark model in the present study since it is also the focus of this document to find if the implied volatility measure of commodities helps improving the forecasting accuracy of the HAR model.

The Heterogeneous Autoregressive (HAR) Model with exogeneous regressors

$$RV_{t+1\,d}{}^{(d)} = \beta_0 + \beta_1{}^{(d)} RV_t{}^{(d)} + \beta_2{}^{(w)} RV_t{}^{(w)} + \beta_3{}^{(m)} RV_t{}^{(m)} + \beta_4{}^{(d)} X_t{}^{(d)} + \varepsilon_{t+1d} \quad (2)$$

For t=1,…,T

Where $RV_{t+1\,d}{}^{(d)}$ is the daily Realised Volatility at the period $_{t+1}$

The $RV_t{}^{(i)}$ denotes each of the Realised Volatility components, *i=d, w, m* for the daily, weekly and monthly components respectively.

The $X_t{}^{(d)}$ is the daily exogenous regressor of Implied Volatility at period $_t$, it represents either the Implied Volatility of the BCOM Commodity market (IV) or the implied volatility from the US stock market (VIX).

The Implied Volatility Model

$RV_{t+1\,d}{}^{(d)} = \beta_0 + \beta_4{}^{(d)} X_t{}^{(d)} + \varepsilon_{t+1d}$ (3)

For t=1,…,T

Where $RV_{t+1\,d}{}^{(d)}$ is the daily Realised Volatility at the period $_{t+1}$

The $X_t{}^{(d)}$ is the daily exogenous regressor of Implied Volatility at period $_t$, it represents either the Implied Volatility of the BCOM Commodity market (IV) or the implied volatility from the US stock market (VIX).

The GARCH (1,1) (Bollerslev, 1986) and EGARCH (1,1) (Nelson and Cao, 1991)

$r_t = \mu + \varphi_1 r_{t-1} \varepsilon_t$ AR (1) for the mean equation

$\varepsilon_t = h_t\, \eta_t \quad \eta_t \sim (0, h_t^2)$ innovation

$h_t^2 = \alpha_0 + \alpha\, \varepsilon_{t-1}^2 + \beta\, h_{t-1}^2$ GARCH variance equation[31]

$\log\,(h_t^2) = \alpha_0 + \alpha\, \frac{|\eta_t|}{\sqrt{h_t^2}} + \gamma \frac{\eta_t}{\sqrt{h_t^2}} + \beta\, ln\,(\,h_{t-1}^2)$ EGARCH variance equation

2.5 Empirical Results

The in-sample results include information for each definition of Realised Volatility measures from July 28, 2011 to Oct 31, 2017. The estimation was made with a Heterogeneous Autoregressive (HAR) model which includes the daily component, weekly and monthly components of each realised volatility.

Table 3 shows that there is an increase in the R^2 of the Heterogeneous Autoregressive (HAR) equation when including the implied volatility estimator in comparison with the standard HAR model. For the case of the Realised Volatility (RV) measured by the squared returns, the standard HAR has a R^2 value of the 0.078 and for the RV model that incorporates the implied volatility measure the R^2 is 0.088

[31] To ensure positiveness of the conditional variance, restrictions on the parameters should be imposed so that the estimators are nonnegative.

registering then a slight improvement, all the regressors except from the daily component are statistically significant at 10 %, in particular the monthly component. The IV and VIX models show that their respective estimators small but statistically significant at usual levels.

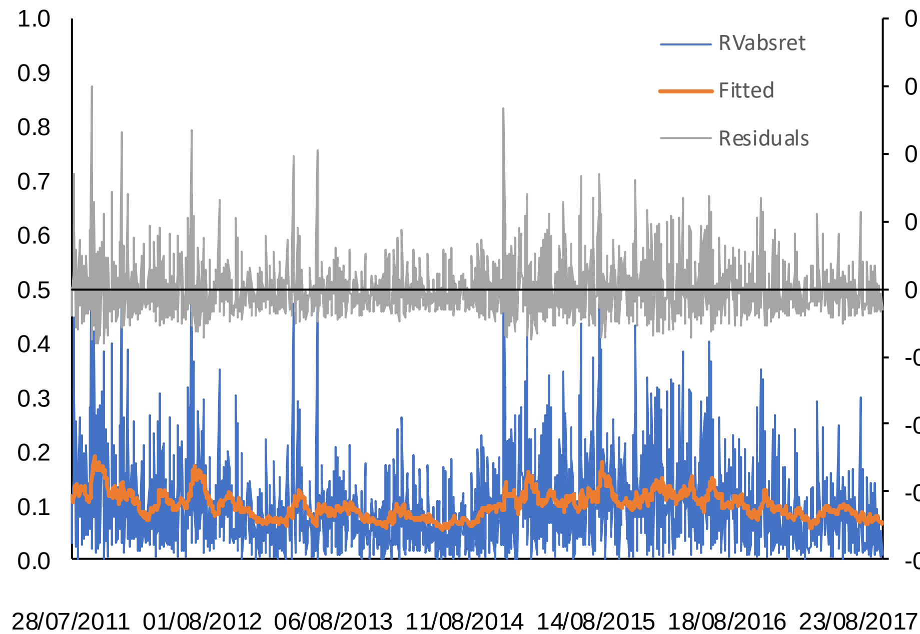
For the Realised Volatility computed with Parkinson´s formula the standard HAR reports an R^2 of 0.249, and the HAR including the implied volatility of commodities has an R^2 of 0.255 and all the regressors apart from the constant for the HAR-IV are statistically significant at 10 %. For both models the estimated coefficients of the HAR components are very similar in magnitude, and the monthly component explains a bigger part (.47) of the Realised Volatility dynamics, followed by the daily (.22) and weekly (.14) components. The implied volatility coefficient estimator is 0.000558. The implied volatility from the Commodity and Stock Markets regressors estimated by equation 3 are also small and statistically significant at 10%.

For the Realised volatility calculated with Rogers´s formula, the standard HAR reports an R^2 of 0.216, and the HAR including the implied volatility of commodities has an R^2 of 0.225 and all the HAR regressors apart from the constant are statistically significant at 10 %. The estimated coefficients of the models are also very similar as in the case of the Parkinson´s measure, where the monthly component explains a bigger part (.48) of the realised volatility dynamics, followed by the daily (.22) and weekly (.11) components. The implied volatility of commodity markets also registers a small coefficient estimator 0.0012 but in this case, it is not statistically significant. For the last alternative Realised Volatility measure, the IV and VIX regressors are also statistically significant at 10%.

Bloomberg Commodity Excess Return (BCOM): Realised Volatility Measures, Fitted and Residuals from the HAR model

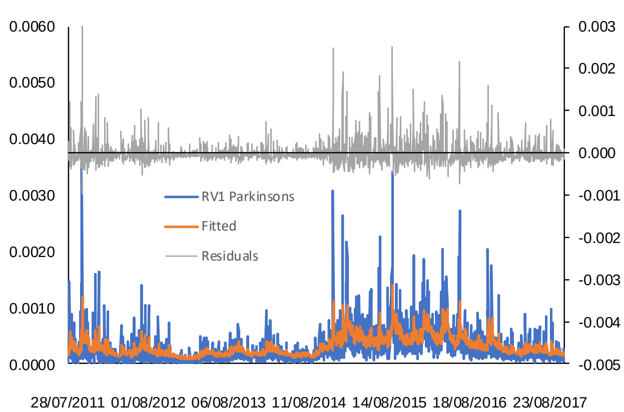
Period from July 28, 2011 to October 31, 2017

Graph 4 Realised Volatility Absolute Returns



Graph 5

Realised Volatility Parkinson



Graph 6

Realised Volatility Rogers

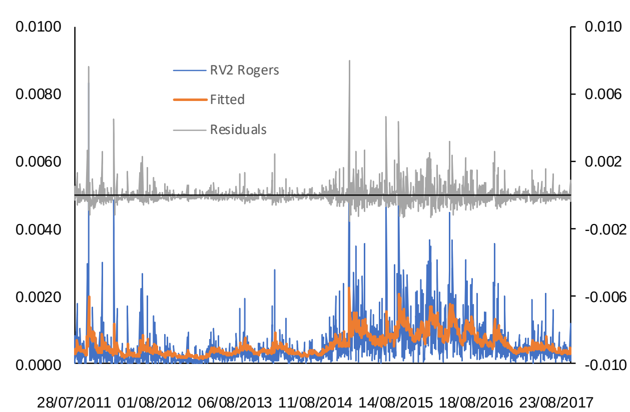


Table 3a. Bloomberg Commodity Excess Return Index: Realised Volatility of the in-sample estimation results

Comparison of Heterogenous Autoregressive (HAR) models and Implied Volatility regressors of the commodity market (BCOM) and the stock market S&P500 (VIX)

	RV Squared Returns				
	HAR	**IV**	**HAR -IV**	**VIX**	**HAR -VIX**
R^2	0.078113	0.049077	0.088284	0.055580	0.087296
F-Statistics	44.484370	81.388280	38.103850	92.689360	37.588830
Prob (Wald-F-Statistics)	(0.000000) *	(0.000000) *	(0.000000) *	(0.000000) *	(0.000000)
AIC	-2.124069	-2.095591	-2.133897	-2.101721	-2.132076
BIC	-2.110479	-2.088796	-2.116909	-2.094919	-2.115072
β_0	0.029940	0.046558	0.015692	0.042531	0.017982
Constant	(5.823191) *	(6.527605) *	(2.53972)	-	(2.536913)
β_1	-0.015726	-	-0.017641	-	-0.018553
Daily comp	(-0.459241) *	-	(-0.545296) *	-	(-0.573267)
β_2	0.173353	-	0.134001	-	0.139217
Weekly comp	(2.042002) *	-	(1.9504) *	-	(1.916034)
β_3	0.540704	-	0.446971	-	0.414426
Monthly comp	(8.177749) *	-	(7.15678) *	-	(5.169927)
β_4		0.369085	0.191366	-	-
I.volatility	-	(7.565128) *	(3.991303) *	-	-
β_5	-	-	-	0.354897	0.174771
VIX (stock market)	-	-	-	(5.921454) *	(3.222768)

The sample estimation period is from July 28, 2011 to October 31, 2017

T-statistics in brackets estimated with Newey-West standard errors to correct for serial autocorrelation based on the AIC.

*Statistically significant at 10 %

The results are computed by estimating the corresponding HAR models according to equation 1, 2 and 3 using OLS for the described Realised Volatility measures.

Source: Own computations with data from Bloomberg, Datastream and Yahoo Finance.

Table 3b. Bloomberg Commodity Excess Return Index: Realised Volatility of the in-sample estimation results

Comparison of Heterogenous Autoregressive (HAR) models and Implied Volatility regressors of the commodity market (BCOM) and the stock market S&P500 (VIX)

	RV Parkinson´s				
	HAR	**IV**	**HAR -IV**	**VIX**	**HAR -VIX**
R^2	0.325890	0.031019	0.328527	0.026616	0.328879
F-Statistics	253.804300	50.483080	192.525000	43.120720	192.832800
Prob (Wald-F-Statistics)	(0.000000) *	(0.000506) *	(0.000000) *	(0.05763) *	(0.000000)
AIC	-3.722553	-3.362235	-3.725206	-3.357701	-3.725731
BIC	-3.708963	-3.355440	-3.708219	-3.350906	-3.708744
β_0	0.009929	0.066673	0.004812	0.068083	0.004069
Constant	(3.276885) *	(11.39932) *	(1.239483)	(5.943262) *	(0.969695)
β_1	0.164779	-	0.161389	-	0.161928
Daily comp	(3.799969) *	-	(3.618566) *	-	(3.76695)
β_2	0.148508	-	0.143795	-	0.132457
Weekly comp	(1.954441) **	-	(1.910946) *	-	(1.840002
β_3	0.57486	-	0.565091	-	0.578544
Monthly comp	(8.644073) *	-	(8.574211) *	-	(8.894989)
β_4	-	0.15430	0.046134	-	-
I.volatility	-	(3.485038) *	(1.643896)	-	-
β_5		-	-	0.129171	0.044309
VIX (stock market)	-	-	-	(1.899887) **	(2.050821)

The sample estimation period is from July 28, 2011 to October 31, 2017

T-statistics in brackets estimated with Newey-West standard errors to correct for serial autocorrelation based on the AIC.

*Statistically significant at 10 %

The results are computed by estimating the corresponding HAR models according to equation 1, 2 and 3 using OLS for the described Realised Volatility measures.

Source: Own computations with data from Bloomberg, Datastream and Yahoo Finance.

Table 3c. Bloomberg Commodity Excess Return Index: Realised Volatility of the in-sample estimation results

Comparison of Heterogenous Autoregressive (HAR) models and Implied Volatility regressors of the commodity market (BCOM) and the stock market S&P500 (VIX)

	RV Roger´s				
	HAR	**IV**	**HAR -IV**	**VIX**	**HAR -VIX**
R^2	0.303906	0.019343	0.307614	0.014367	0.308037
F-Statistics	229.208500	31.104960	174.824900	22.986920	175.172000
Prob (Wald-F-Statistics)	(0.000000) *	(0.000000) *	(0.000000) *	(0.000000) *	(0.000000)
AIC	-3.681536	-3.341331	-3.685611	-3.336270	-3.686222
BIC	-3.667947	-3.334536	-3.668624	-3.329475	-3.669235
β_0	0.009625	0.064591	0.002828	0.06687	0.001885
Constant	(3.704758) *	(10.35256) *	(0.507803)	(6.843049) *	(0.376287)
β_1	0.081469	-	0.077721	-	0.077619
Daily comp	(2.21663) *	-	(2.093098) *	-	(2.097449)
β_2	0.237459	-	0.230669	-	0.220081
Weekly comp	(2.991248) *	-	(3.044661) *	-	(3.044317)
β_3	0.564618	-	0.561956	-	0.577619
Monthly comp	(7.696047) *	-	(8.116135) *	-	(8.63441)
β_4	-	0.122391	0.054202	-	-
I.volatility	-	(2.36215) *	(1.189513)	-	-
β_5	-	-	-	0.095327	0.051691
VIX (stock market)	-	-	-	(1.595184) *	(1.739226)

The sample estimation period is from July 28, 2011 to October 31, 2017

T-statistics in brackets estimated with Newey-West standard errors to correct for serial autocorrelation based on the AIC.

*Statistically significant at 10 %

The results are computed by estimating the corresponding HAR models according to equation 1, 2 and 3 using OLS for the described Realised Volatility measures.

Source: Own computations with data from Bloomberg, Datastream and Yahoo Finance.

In- sample results displayed on Table 3, show that for each of the three Realised Volatility measures, the better ranking models from Implied Volatilities and HAR specifications, are the ones that include the Heterogeneous Autoregressive specification (HAR) based on the AIC and BIC. For the daily absolute returns, the best model is the HAR-IV followed by the HAR, for the Parkinson´s and Roger's log range estimators is HAR-IV followed by HAR-VIX.

The R^2 of the HAR specifications registers bigger values for the Realised Volatility measures of Parkinson's and Roger´s this can be explained graphically. As illustrated by Graph 4, 5 and 6, the model specifications including either one of the latter volatility proxies tend to capture better the volatility dynamics than the absolute daily return, whereas the implied volatility predictors do not capture differently the volatility dynamics across proxies[32]. Viteva et.al (2014) also mentioned that that the R^2 is expected to be greater when using the log range estimators relative to the squared returns although they regress the RV on a constant and any of the two alternative measures of Implied Volatility for the commodity and stock market.

Table 3d. Bloomberg Commodity Excess Return Index: Realised Volatility of the in-sample estimation results

Comparison of GARCH (1,1) and EGARCH (1,1) models of log returns of the commodity market (BCOM)

	Mean equation			
	GARCH(1,1)		EGARCH(1,1)	
μ	-0.000331		-0.000376	
Constant	(-1.870347)	*	(-2.096661)	**
θ	-0.011637		-0.014415	
AR(1) comp	(-0.460666)		(-0.589261)	
AIC	-6.873349		-6.871802	
BIC	-6.852954		-6.848007	
LogLikelihood	5429.073		5428.852	
	Variance equation			
ω	0.0000005		-0.118098	
Constant	(1.83797)	*	(-2.934828)	**
α	0.0486600		0.079997	
ARCH(1)	(4.660504)	**	(4.409465)	**
β	0.9444170		0.994402	
GARCH (1)	(83.52908)	**	(288.886)	**
ϒ	-		-0.031534	
Leverage	-		(-2.924125)	**
T dis DOF	9.680200	**	9.958056	**
	(5.804846)		(5.328369)	
	Residuals Diagnosis			
Q-stat lag 20	10.034000		10.149000	
p-value	(0.968)		(0.965)	
ARCH LM Test	-			
p-value	(0.8217)		(0.26)	

The sample estimation period is from July 28, 2011 to October 31, 2017

Z-statistics in brackets estimated with Newey-West standard errors to correct for serial autocorrelation based on the AIC.

[32] Graphics not shown.

T- distribution Degrees of Freedom

*Statistically significant at 10 %

**Statistically significant at 5 %.

The results are computed by estimating the corresponding GARCH(1,1) and EGARCH(1,1) models according to equation x, using MLE Students's T distribution (To account for non- normality features) for the logreturns

Source: Own computations with data from Bloomberg, Datastream and Yahoo Finance.

The GARCH specifications are used to get the one step- ahead conditional volatility forecasts from GARCH(1,1) and EGARCH(1,1) in order to assess the forecasting accuracy of the GARCH component in forecasting the one step ahead Realised Volatility Proxies, which are conditionally unbiased estimators of the true and latent conditional volatility. The GARCH forecasts are obtained following a rolling window worth of 1,000 data.

Forecasting accuracy

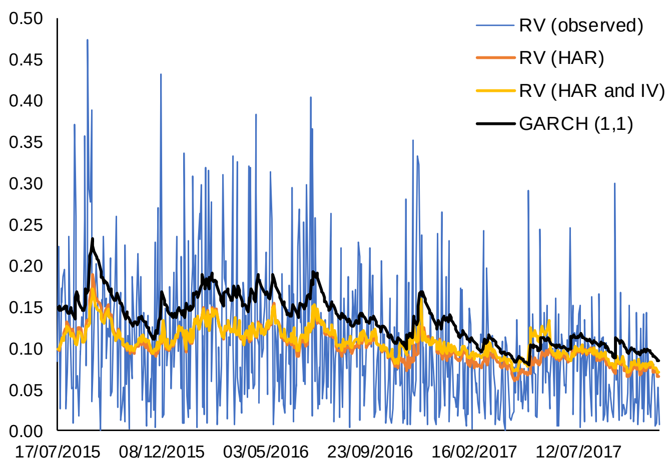
On the other hand, regarding the one-day ahead out of sample forecasts for each measure of Realised Volatility are estimated following a rolling window of size 1,000 days of data (See Corsi, 2009, and Patton 2011) for the period from March 3, 2016 to October 31, 2017. Following Equations 1,2, 3 and x of the Methodology section 3.

The HAR model can capture some of the dynamics of the volatility of Commodity Prices, overall for the Parkinson's definition if one includes the daily component of Implied Volatility of the underlying BCOM into the HAR forecasting equation, as displayed in the following Graphs.

Bloomberg Commodity Excess Return (BCOM): Realised Volatility Measures and their Daily Forecast

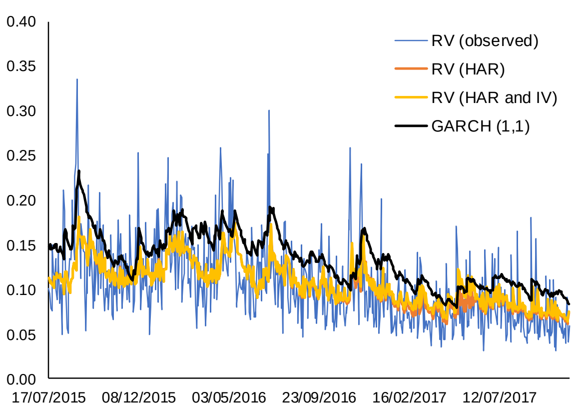
One-day ahead forecast period from July 17, 2015 to October 31, 2017

Graph 7 Realised Volatility Absolute Returns



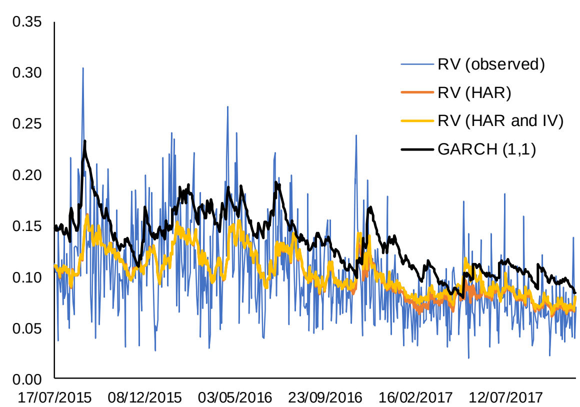
Graph 8

Realised Volatility Parkinson



Graph 9

Realised Volatility Rogers



The one-day ahead out of sample forecasts were estimated for the period starting from 17/07/15 to 31/10/17 from the HAR equation with a rolling window method (window size of 1000 days of data).
RV (observed) corresponds to the actual value of the corresponding Realised Volatility measure.
RV (HAR) corresponds to the benchmark forecast of the HAR model for each of the corresponding Realised Volatility measures.
RV (HAR and IV) corresponds to the forecast of the HAR model including the Implied Volatility (IV) measure for each of the corresponding Realised Volatility measures.
RV GARCH (1,1) corresponds to the forecast of the GARCH (1,1) for each of the corresponding Realised Volatility measures.

Source: Own computations with data from Bloomberg and Datastream

Table 4a

RMSE one-step ahead out - sample daily forecasts, rolling window

					Alternative Models vs GARCH (1,1) Percentage Ratios		
Periods	**RMSE**	**RV Squared Returns**	**RV Parkinson´s**	**RV Roger´s**	**RV Squared Returns**	**RV Parkinson´s**	**RV Roge**
	IV	0.090363	0.048181	0.048897	93.54	89.10	86
	VIX	0.091592	0.054170	0.055592	94.81	100.17	98
Mar 16 - Dec 16	HAR -IV	0.089778	0.043116	0.044410	92.93	79.73	78
	HAR	0.090239	0.043209	0.044559	93.41	79.90	79
	GARCH(1,1)	0.096605	0.054077	0.056341	**100.00**	**100.00**	**100**
	E-GARCH(1,1)	0.094795	0.050956	0.052644	98.13	94.23	93
	IV	0.066419	0.044015	0.040341	101.75	109.68	100
	VIX	0.058701	0.030522	0.027677	89.93	76.06	69
Jan 17- Oct17	HAR -IV	0.060326	0.031284	0.028491	92.42	77.96	71
	HAR	0.058979	0.030555	0.027212	90.36	76.14	68
	GARCH(1,1)	0.065274	0.040129	0.040019	**100.00**	**100.00**	**100**
	E-GARCH(1,1)	0.064819	0.039655	0.039477	99.30	98.82	98
	IV	0.079234	0.046095	0.044781	96.18	96.89	91
	VIX	0.076872	0.043940	0.043891	93.31	92.36	89
3/03/16- Oct 17	HAR -IV	0.076426	0.037636	0.037284	92.77	79.11	76
	HAR	0.076174	0.037391	0.036895	92.47	78.59	75
	GARCH(1,1)	0.082380	0.047576	0.048827	**100.00**	**100.00**	**100**
	E-GARCH(1,1)	0.081140	0.045616	0.046489	98.50	95.88	95

Ratios below 100 indicate that the competing model outperform the benchmark GARCH (1,1).
Source: Own computations with data from Bloomberg and Datastream.

The out-sample results for the daily forecasts for each definition of Realised Volatility show that the inclusion of the implied volatility measure slightly improves the daily forecast during 2016, registering ratios under 100 in comparison with the GARCH (1,1) for the third Volatility Measure (Rogers'). The general conclusion is that for all the Volatility Proxies, the HAR model's forecast outperforms the competing models' forecasts and the benchmark GARCH (1,1) for all the periods, except for the most recent period Jan17-Oct17 where the VIX model together with the HAR model outperform the GARCH (1,1). For the Realised Volatility measured as absolute returns similar results are obtained but the difference in magnitudes among competing models is less evident relative to the range-based estimators as illustrated by Table 4a.

Table 4b

RMSE one-step ahead out – sample daily forecasts, rolling window

Periods	RMSE	RV Squared Returns	RV Parkinson´s	RV Roger´s	RV Squared Returns	RV Parkinson´s	RV Roge
					Alternative Models vs E-GARCH (1,1) Percentage Ratios		
	IV	0.090363	0.048181	0.048897	95.33	94.55	92
	VIX	0.091592	0.054170	0.055592	96.62	106.31	105
Mar 16 - Dec 16	HAR -IV	0.089778	0.043116	0.044410	94.71	84.61	84
	HAR	0.090239	0.043209	0.044559	95.19	84.80	84
	GARCH(1,1)	0.096605	0.054077	0.056341	101.91	106.12	107
	E-GARCH(1,1)	0.094795	0.050956	0.052644	**100.00**	**100.00**	**100**
	IV	0.066419	0.044015	0.040341	102.47	110.99	102
	VIX	0.058701	0.030522	0.027677	90.56	76.97	70
Jan 17- Oct17	HAR -IV	0.060326	0.031284	0.028491	93.07	78.89	72
	HAR	0.058979	0.030555	0.027212	90.99	77.05	68
	GARCH(1,1)	0.065274	0.040129	0.040019	100.70	101.19	101
	E-GARCH(1,1)	0.064819	0.039655	0.039477	**100.00**	**100.00**	**100**
	IV	0.079234	0.046095	0.044781	97.65	101.05	96
	VIX	0.076872	0.043940	0.043891	94.74	96.33	94
3/03/16- Oct 17	HAR -IV	0.076426	0.037636	0.037284	94.19	82.51	80
	HAR	0.076174	0.037391	0.036895	93.88	81.97	79
	GARCH(1,1)	0.082380	0.047576	0.048827	101.53	104.30	105
	E-GARCH(1,1)	0.081140	0.045616	0.046489	**100.00**	**100.00**	**100**

Ratios below 100 indicate that the competing model outperform the benchmark E-GARCH (1,1).
Source: Own computations with data from Bloomberg and Datastream.

Since the E-GARCH (1,1) forecasts outperform the other benchmark's forecasts GARCH (1,1), results are less powerful in comparison with the GARCH (1,1) but confirm the aforementioned findings, as displayed by Table 4b. Throughout the whole period from March 2016 to October 2017 and for the subperiod March 2016 to December 2016 the HAR and HAR-IV specifications offer better forecasts than the E-GARCH (1,1) and contending models. For the subperiod January 2017 to

October 2017 the HAR and VIX models display the smaller ratios relative to the benchmark and other models. These results are particularly true for the Roger's measure of realised volatility and less strong for the squared returns measure.

Another frequently measure used to assess the forecasting accuracy of competing models, and in particular of volatility forecasts is the Mincer-Zarnowitz regressions. The corresponding regression R^2 results are shown on Table 5 and tend to agree with in-sample and pseudo-out sample MSE analysis, where the HAR models are preferred over the implied volatilities and even over the GARCH (1,1) and E-GARCH(1,1) specifications in the case of Parkinson's measure of Realised Volatility.

Table 5a

Forecasting comparison with the R^2 of the Mincer-Zarnowitz regressions[33]

Periods	R^2	RV Squared Returns	RV Parkinson´s	RV Roger´s
3/03/16- Oct 17	IV	0.019	0.001	0.0001
	VIX	0.044	0.018	0.0025
	HAR -IV	0.057	0.225	0.1922
	HAR	0.051	0.228	0.1981
	GARCH(1,1)	0.060	0.223	0.2315
	E-GARCH(1,1)	0.056	0.211	0.2265

The sample corresponds to the forecasting sample of 421 data which spans from March 2016 to October 2017. Highlighted values in blue show the higher R^2 of the Mincer-Zarnowitz regressions for each of the three Realised Volatility measures.

33 From Corsi (2009) the Mincer-Zarnowitz regression is a regression of the ex post realised volatility on a constant and the competing models forecasts based on time t-1 data.

$$RV_t^{(d)} = b_0 + b_1 \mathrm{E}_{t-1}\left[\left(\widehat{RV}_t^{(d)}\right)\right] + \varepsilon$$

Table 5b shows the Diebold-Mariano test statistics which confirm the findings that the HAR and HAR-IV models provide with forecasts that are statistically significant more accurate than the respective benchmarks GARCH (1,1) and E-GARCH(1,1). Forecasts from models which include either the Implied Volatility measure or the VIX are not statistically significant more accurate than the benchmarks. A comparison between the benchmarks tends to prefer the forecasts from E-GARCH (1,1) instead of the GARCH (1,1) forecasts.

Table 5b

Forecasting comparison Diebold-Mariano Test[34]

		RMSE percentage ratio Relative to GARCH (1,1)			Diebold- Mariano Test Statistics					
Periods	**Model**	**RV Squared Returns**	**RV Parkinson´s**	**RV Roger´s**	**RV Squared Returns**		**RV Parkinson´s**		**RV Roger´s**	
	IV	96.18	96.89	91.71	-1.87		-0.82		-1.91	
	VIX	93.31	92.36	89.89	-2.41	*	-1.66		-1.86	
03/03/16- Oct 17	**HAR -IV**	92.77	79.11	76.36	-4.34	*	-7.94	*	-7.59	*
	HAR	92.47	78.59	75.56	-4.05	*	-7.90	*	-7.64	*
	GARCH(1,1)	**100.00**	**100.00**	**100.00**	-		-		-	
	E-GARCH(1,1)	98.50	95.88	95.21	-2.99	*	-4.29	*	-4.70	*
			Model vs E-GARCH (1,1)							
	IV	97.65	101.05	96.33	-1.24		0.28		-0.88	
	VIX	94.74	96.33	94.41	-2.02	*	-0.81		-1.01	
03/03/16- Oct 17	**HAR -IV**	94.19	82.51	80.20	-4.05	*	-7.41	*	-6.97	*
	HAR	93.88	81.97	79.36	-3.71	*	-7.34	*	-7.00	*
	GARCH(1,1)	101.53	104.30	105.03	2.99	*	4.29	*	4.70	*
	E-GARCH(1,1)	**100.00**	**100.00**	**100.00**	-		-		-	

*Statistically significant at 1%.
*Forecasts spans Mar16-Oct17 estimated with a Rolling a window of 1,000 daily data.
Root Mean Squared Error (RMSE) of the 1 step ahead out-of-sample forecast of the respective model and the corresponding daily Realised Volatility Proxies of the BCOM.
GARCH (1,1) and E-GARCH (1,1) denote the 1- step ahead forecast of conditional volatility.
Ratios under 100 show that the alternative outperforms the benchmarks GARCH (1,1) or E-GARCH (1,1).

[34] The Diebold- Mariano test statistics tests the null hypothesis that the differential loss 'd' equals zero, this loss is denoted as the difference of squared forecast errors between two competing models. Under the stationarity assumption of the differential process 'd'. (For further information see Patton, 2011).

Negative values of the DM t-statistics mean that the alternative model generates lower loss relative to the benchmark model, on average.

2.6 Conclusion

This study has evaluated the forecasting accuracy of competing models that forecast three measures of daily realised volatility of the global commodity index: the Bloomberg Commodity Index Excess return (BCOM). The scope of this document includes traditional benchmark models to forecast volatility such as GARCH (1,1) and E-GARCH (1,1), plus other models which contain implied volatility measures for at the money call options of the Dow Jones-UBS Commodity Index, and from the US stock market (VIX); and the Heterogeneous Autoregressive Model (HAR). A novelty of this empirical exercise is the use of non-parametric range estimators as volatility proxies in the context of forecasting daily realised volatility of a Global Commodity Index Returns.

In-sample analysis shows the HAR components are statistically significant and offer a considerable higher R^2 relative to the models that only include the implied volatilities from the commodity and stock markets. The IV of BCOM if statistically significant it a biased estimator of the Realised Volatility which is measured by the three volatility proxies: absolute returns and Parkinson's and Rogers range estimators, and on it is own does not improve the forecasting accuracy of the daily Realised Volatility of Global Commodity Returns, but when the implied volatility of the commodity markets is included to the HAR specification the R^2 increases slightly.

Out-of sample analysis requires to compare the forecasting accuracy of the contending models, and hence, their respective Root Mean Squared Error (RMSE) were computed. Based on this metrics the HAR and HAR-IV specifications offer more accurate forecast of the three measures of Realised Volatility of Global Commodity Returns in comparison with benchmark models such as GARCH(1,1) and E-GARCH (1,1), these findings are statistically significant based on the Diebold-Mariano test statistics. The aforementioned results are more prominent for the range estimators of realised volatility.

Chapter 3

3. Granger Causation between speculative measures and the log returns or realised volatility of wheat futures prices

3.1 Introduction

Commodity prices have gained popularity for investors and fund managers, with an observable increase of investors who use commodity assets not only for hedging or speculation purposes, but also as a tool to diversify away the risk of diversified stock/bond portfolios. Consequently, and in particular with respect to diversifying characteristics of commodity prices, understanding the drivers of commodity futures markets is relevant to investors, policy makers, and other market participants Andreasson, Bekiros, Nguyen and Uddin, (2016).

The co-movement between commodity futures and financial assets has been researched by the literature (e.g., Büyüksahin and Robe 2014), but exploring causality between commodity futures and their potential driving factors - fundamentals and speculation, - has received less attention. Overall there is much less work on studying causality between commodity futures and potential drivers on volatility relative to returns. In addition, the role of speculation as a driving factor of commodity futures returns and volatility has not been explored extensively.

In this regard, with respect to the role of speculation on commodity prices, Masters states that (as cited in Irwin and Sanders, 2011) the massive index fund buying during 2003-2007 created a "bubble" that forced commodity futures prices above their fundamental values. This "bubble" is based on two principles: first, fundamentals cannot explain the price level; and second trading is not based on the fundamental values. However, some criticisms have arisen regarding the empirical validity of the effect of index fund investment on commodity futures prices. For instance, Irwin and Sanders (2011) argue that the empirical evidence relative to Masters' hypothesis is limited, due to the statistical mistake of confusing correlation with causation between money flows and prices.

Hence, the present study aims to contribute to the literature in this way: the focus of this document will be exploring the causal relationship between speculative measures: Working's T-Index and the log change of weekly managed money spreading positions, -as defined by Singleton (2014) and reported by the U.S Commodity Futures Trading Comission (CFT)-, and the log of a realised measure of weekly volatility of the futures prices of wheat from Chicago Board of Trade. The aim is to explore the potential causal relationship of speculative measures as potential drivers of both the volatility and returns of wheat futures prices.

The study is organized in five sections. The first section describes the previous literature regarding the impact of speculation on commodity futures returns, including agricultural commodities. The literature may be divided into two branches. The first supports the claim that there is a link between a definition of "excess speculation" measured by the Working's T-Index, and commodity futures returns. For instance, Andreasson et al. (2016) found a strong linear causal relationship between the commodity futures returns and "excess speculation", being particularly true for the agricultural commodities. On the other side, authors such as Irwin and Sanders (2011) have cast doubt regarding the Masters' hypothesis by arguing there is no compelling evidence of the effect of the index fund investment on commodity futures dynamics.

Section two describes the data used to study the effect of speculation on futures returns, using weekly data of continuous wheat futures prices from DataStream, and the weekly realised volatility of Wheat Chicago Board of Trade. The weekly realised volatility is computed according to Rogers and Satchell's (1991) formula of daily volatility which is aggregated into weekly volatility and annualized. As proxies of speculation I use the Working's T- Index, which is the most popular measure of speculation used to study causality, and the alternative proxy: managed money spreading positions obtained from the Disaggregated Report Commitments of Traders (COT), based on Singleton's (2014) evidence where hedge funds spread trading impacted oil futures returns in a direct manner during the boom prices of 2008.

The methodological framework is described in section Three. Granger causality tests are based on the bivariate vector autoregressive model (VAR). In order to estimate the effect of each of the aforementioned speculative measures on the log realised volatility and log returns of wheat futures prices in a weekly basis. Section Four presents the empirical results of estimating the corresponding bivariate vector autoregressive (VAR), over a weekly period that spans from January 15, 2008 to June 5, 2018. Findings suggest there is statistically significant unidirectional linear causality from the change in managed money to both log realised volatility and log returns. In contrast, when the speculative measure is the Working's T-Index the unidirectional linear causality comes from both log returns and log realised volatility to "excess speculation". Finally, Section Five presents the main conclusions.

3.2 Literature Review

3.2.1 Causality between economic and speculative driving factors and commodity prices

Andreasson et al. (2016) highlighted the fact that the previous literature (e.g., Bekiros and Dicks 2008) has explored the co-movement between commodity futures, spot prices, and economic fundamentals, with contradictory empirical findings. However, little emphasis has been paid to the study of both linear and non-linear causal relationships between commodity futures and their potential drivers. Thus, the aforementioned authors studied the linear and non-linear relationships between commodity futures returns and five drivers: financial speculation was measured by the Commodity market speculation index represented by the Working's T Index, and the other factors were exchange rate, stock market dynamics, economic policy uncertainty and implied volatility for the US stock market. They implemented nonlinear causality tests over the period May 1990-April 2014, which results show evidence of non-linear causality between equity returns and implied volatility and between commodity futures returns; and unidirectional linear causality from commodity returns to excess speculation for the greater part of the commodities, being particularly the case for agriculture commodities. Then giving supporting evidence against speculation as a main factor impacting food prices.

In relation to the impact of speculation on diverse commodity prices some studies are available. For instance, for the oil futures market, Fattouh, Kilian and Mahadeva (2012) explain that financialization of futures markets is understood as index funds taking speculative positions (long/short), which first make the oil futures prices to surge and then caused a similar increase in spot oil prices. To these authors what matters is the net positions financial investors are taking and how they are impacting the risk aversion, horizon and risk-bearing capacity of all traders.

Singleton (2014) argues that speculation is described by examining the source of variation of oil futures risk premia. Given limits to arbitrage, heterogeneous beliefs among investors can impact positively commodity prices because there is a connection between the risk bearing capacity of broker dealers and risk premia. Thus, the structural vector autoregressions SVAR used by Kilian and others are not sufficient to disentangle the importance of the risks connected with shock effects to fundamentals from the effects of price drift due to speculations based on different interpretations of fundamental shocks. Singleton presents economically and statistically significant evidence of the effects of investors flows on oil futures prices. Then, index-investors and managed money spreading positions[35] -as speculative measures- rather than fundamentals explain the high variation in oil futures prices during high uncertainty periods.

---

[35] According to the Commodity Futures Trading Comission (CFT) and the *Disaggregated Commitments of Trader Report* , "…the 'money manager' is a registered commodity trading advisor (CTA); a registered commodity pool operator (CPO); or an unregistered fund identified by CFTC. These traders are engaged in managing and conducting organized futures trading on behalf of clients….
"Spreading" is a computed amount equal to offsetting long and short positions held by a trader. The computed amount of spreading is calculated as the amount of offsetting futures in different calendar months or offsetting futures and options in the same or different calendar months..."
(Available at:
https://www.cftc.gov/sites/default/files/idc/groups/public/@commitmentsoftraders/documents/file/disaggregatedcotexplanatorynot.pdf, pp. 2-3).

In contrast, Irwin and Sanders (2011) argued that there is a lack of a direct empirical link between index fund trading and commodity futures price returns. However, they also acknowledge that one branch of the literature does find evidence of index fund trading having an impact on futures prices. In this regard, several papers showed that investments in long-only commodity index funds can benefit from risk premiums and reduce portfolio risk in concordance with Master's hypothesis. Some direct effects of the impact of speculation on commodity prices are described by the U.S. Senate Permanent Subcommittee on Investigations of the performance of the CBOT wheat futures contract, which found in 2009 that commodity index traders considered as "excessive speculation" were one of the main causes of price disparity between wheat futures prices and the wheat spot price. Hence, recommending different restrictions on index traders.

3.2.2 The role of fundamentals as drivers of commodity prices

Nevertheless, from a more fundamentalist approach Irwin and Sanders (2011) have argued that commodity markets in 2007-2008 were driven by fundamental supply and demand factors such as strong demand from China, India and other developing countries, and the US monetary policy among others. This argument is also consistent with Tang and Xiong (2010) who argue that the financialization of commodity markets measured by the index investment is an effect of a fundamental process related for example to the recent economic recession, which has caused an increase in the correlation of commodity markets with each other, overall with the crude oil, stocks, bonds and the U.S. dollar.

Frankel (2006) studies the impact of monetary policy on US and other countries commodity prices. The theoretical hypothesis that was tested empirically is that loose monetary policy -understood by low real interest rates, - lead to high real agricultural and mineral commodity prices. Low real interest rates lower the cost of carry inventories and hence cause a rise on real commodity prices. Frankel like Kilian (2014) also acknowledge the impact of growing demand from emerging countries on commodities prices during 2004-2006.

Frankel and Rose (2009) present a theory that studies the impact of macro and microeconomic fundamentals on annual real spot prices of agricultural, livestock, energy and metal commodities, for the period which spans from 1960 to 2008. The macroeconomic elements are the global GDP and real interest rate; and the microeconomic fundamentals are represented by inventory levels, measures of economic uncertainty and the spot forward spread. Main findings indicate positive effects from both micro and macro factors on real commodity prices, highlighting the role of micro factors on prices.

Another important advocate of the fundamentalist approach is Kilian (2014) who argues that given the endogenous nature of oil spot prices, it is necessary to use structural models to disentangle the causal relationship between oil prices and the economy. His study focuses on measuring the effect of supply, flow demand and speculative demand -understood through inventories, -, on US oil spot prices. The main findings for the period 2003-2008 show that flow demand and not speculative demand was the main factor driving prices to surge due to the fast economic growth from China and India particularly.

3.2.3 Determinants of volatility of commodity futures prices.

Given the considerable debate in the literature with respect to what were the driving forces determining the changes in prices and volatilities of commodity markets - fundamentals or speculation, -, it makes sense to study whether speculation causes commodity futures volatility or not. The majority of the literature has been devoted to study the interaction between speculation and commodity futures and spot markets, with focus on studying the impact of speculation on commodity futures returns to study the potential drivers of commodity in a co-movement framework rather than exploring potential causal relationships.

Some studies have explored the determinants of the volatility of commodity futures returns. Mo, Gupta, Li & Singh (2018) focus on the macroeconomic determinants of volatility of commodities which include agricultural, metal and oil. These macroeconomic determinants include both domestic and international variables that signal economic environment, monetary policy and financial market information in India and China using a GARCH MIDAS model. In another article, Feng and Chuan-Ze (2008) try to study empirically the determinants of the volatility such as time to maturity, the day of week effect, volume and open interest, of wheat futures returns in China, with a GARCH framework.

Hasse and Huss (2018) study whether excess speculation is responsible for excess volatility on wheat futures contracts traded at five commodity exchanges with various degrees of speculative activity. The excess volatility is estimated based on the Conditional Autoregressive Range Model (CARR). Their findings evidence that speculation diminish wheat volatility, and that some degree of excess speculation it is crucial for a market to function properly. However, to the best of my knowledge none or little has been said with regards to the study of the causal relationships between speculation and volatility of commodity futures.

Analysing the volatility behaviour of an agricultural commodity, like wheat, has implications not only for hedgers, speculators and investors. As stated by Hasse and Huss (2018), there are some political and socio-economical implications, for example, United Nations works actively to limit the potential risk coming from agricultural prices volatility because it can impact not only the general level of prices but also threaten food security. Making essential to assure the proper functioning of agricultural commodity markets. In addition, understanding volatility helps hedgers in managing their production risk and making marketing decisions, and it also aids investors in the decision-making process.

Agricultural commodities such as wheat futures contracts at the Chicago Board of Trade have been exposed to the inflow of index investments, and the Chicago Wheat contract has always been a substantial part of all major commodity indices such as the S&P Goldman and Sachs Commodity Index (GSCI) and The Bloomberg Commodity Index (BCOM) whose weight ranges between 3.8% and 3.3% respectively, according to the GSCI (2016) and BCOM (2017) methodological documents. Because of the aforementioned reasons, studying causality between wheat futures returns and the realised volatility and speculative measures makes sense and therefore is the aim of this document.

3.3 Data

The weekly wheat futures returns I examine is the weekly log return defined as the return[36] using weekly data of continuous wheat Chicago Board of Trade (CBOT) futures prices from DataStream, whose perpetual series are derived from single futures contracts starting from the nearby contract month, based on the rollover on the 1st business day of the new contract month. The realised volatility of the futures prices of wheat of CBOT is estimated following Rogers and Satchell's formula of daily volatility, which is as an unbiased proxy of unobserved volatility. In absence of higher frequency intraday data the range price estimator is more efficient than the daily squared return in the sense of having a smaller Mean Squared Error MSE, and thus is preferred over the daily squared return as a volatility proxy. (see Viteva, 2014).

Rogers and Satchell´s (1991) daily volatility

$$\sigma_d^2 = \ln\left(\frac{high_t}{open_t}\right)\ln\left(\frac{high_t}{close_t}\right) + \ln\left(\frac{low_t}{open_t}\right)\ln\left(\frac{low_t}{close_t}\right) \qquad (\mathbf{1})$$

Then, in order to construct the weekly volatility measure of futures prices of wheat I just simply add up the daily volatilities of the corresponding week. Some months consist of five weeks, but I balance the data to have four weeks intervals of seven and eight days until the third week, and by including up to two more days on the fourth week.

[36] The weekly log return is defined as follows: $R_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$, where P_t denotes the closing price of a given week, and P_{t-1}, represents the closing price of the immediate previous week.

$$\sigma_w^2 = \sum_{i=1}^{n} \sigma_d^2$$

And finally, following financial literature conventions, I annualize the weekly volatility calculating the next formula:

$$\sigma_t = \sqrt{252/n} * \sqrt{\sigma_w^2}$$

Where *n*=number of working days for the respective week

The novel aspect of the present study is the use of Managed Money Spreading Positions[37] as one of the speculative measures of wheat futures prices in the context of causality between speculation and returns, and volatility. Managed Money spreading positions are taken from the 22 agricultural commodity future markets of the weekly disaggregated Futures Commitments of Traders (COT) reports. As displayed in Table 1. Four categories of traders are reported: Producer/Merchant/Processor/User; Swap Dealers; Managed Money; and Other Reportables.

According to Singleton (2014) speculative measures such as index traders and managed money spreading positions have economical and statistically significant effects on oil futures prices through risk and informational routes, different from convenience yield dynamics. This informational route is explained by the fact that index funds investments and managed money positions contain information about the subjective interpretation of heterogeneous beliefs of supply and demand on the oil futures market.

One of the main criticisms against the effect of speculation on commodity futures prices has been that index investment is not completely speculative or directed entirely by portfolio diversification, but by a more fundamentalist approach, where

[37] According to the Disaggregated Commitments of Traders (Disaggregated COT), Managed Money are professional traders such as a registered commodity trading advisor (CTA); a registered commodity pool operator (CPO); or, and unregistered hedge funds, whose strategy is to manage and organize trading on behalf of their clientele.

index investment is not a driven force, but it rather reflects fundamentals factors. For example, Gilbert (as cited in Irwin and Sanders, 2011) states that agricultural price booms are better explained by common demand factors from a rapid growth in Asian developing economies and the dollar depreciation.

Hence, considering these findings, it makes sense to test the effect of managed money spreading positions on wheat futures log returns and their log realised volatility. Since one of the main purposes of managed money clientele is obtaining the benefits of diversification, thus managed money can better represent speculation. Just as Singleton (2014) I also chose money spreading positions because they influence commodity futures prices through affecting the risk premium, and also due to the high activity of hedge funds on spread trade, which as stated by Singleton (2014) a spread trade means to be long and short simultaneously at different points of the futures term structure.

Due to data limitations, to match the samples of the speculative measures and the log realised volatility of wheat futures prices. The sample period cannot start before June 2006, because the disaggregated futures reports are available from that date. However, in this empirical exercise, to capture the dynamics starting from the 2008 financial crisis the sample period will span from January 2008 to June 2018.

In order to match the samples of the speculative measures and the log realised volatility of futures wheat futures prices. The sample period will span from January 2008 to June 2018. The initial starting point is 2008 to capture the beginning of the 2008 financial crisis, however, the dissagregated futures reports are available from June 2006.

Following Working's (1960) methodology I compute the second speculative measure, the Working's T index, which is broadly used in the financial literature to measure the degree of excess speculation relative to hedging activity in the markets. In fact, this measure has been a benchmark in the literature to study the effect of speculation on commodity futures prices and causality linkages between speculation and commodity futures return. For instance, Andreasson et.at.al. (2016) measured the impact of speculation using the Working's T-Index as proxy, similarly to Irwin and

Sanders (2011) among others. The data I used to compute the Working's T-Index is from the Commitments of Traders (COT) reports which provide with data about hedgers and speculators positions of various commodities, including wheat from Chicago Board of Trade (CBOT).

I compute the Working's T index as follows:

$$WT = 1 + \frac{SS}{HL + HS} \; if \; HS \geq HL$$

$$WT = 1 + \frac{SL}{HL + HS} \quad otherwise$$

where SS denotes short positions held by speculators measured by the non-commercial short positions of the COT reports, SL denotes the corresponding long speculative positions. Likewise, HS and HL denote the number of short and long positions held by hedgers which are described by commercial positions according to the CFTC.

3.3.1 Data Features and Descriptive Statistics

Table 1 displays the descriptive statistics of the log returns and the log realised volatility of wheat futures prices from the Chicago Board of Trade (CBOT), as well as the two speculative measures: log change of managed money spreading positions and the D(Working's T Index), over the period January 15, 2008 to June 5, 2018, at the weekly frequency.

Table 1 Descriptive Statistics of the log returns, Rogers realised volatility, and the log change of managed money spreading positions of wheat futures prices, at weekly frequency

	Log returns	Realised Volatility Rogers	Log Realised Volatility Rogers	Managed Money Spreading Positions (Log change)	Working T Index	D(Working T Index)
Mean	-0.0010010	0.2978310	-1.2797370	0.0010370	1.3163800	0.0001800
Median	-0.0054110	0.2712670	-1.3046530	0.0066860	1.2950000	0.0000000
Maximum	0.2293650	1.4508950	0.3721800	0.5029360	1.6400000	0.0800000
Minimum	-0.1762510	0.1055480	-2.2485920	-0.4758940	1.1400000	-0.1100000
Std. Dev.	0.0500950	0.1242750	0.3589330	0.1173300	0.1213530	0.0224000
Skewness	0.4633910	2.6600220	0.4603790	-0.2956190	0.4262050	-0.3101310
Kurtosis	4.8636290	18.9996500	3.7224470	4.6288000	2.1315300	5.9478000
Jarque-Bera	90.25078	5922.741	28.53591	62.55315	30.85089	188.6688
Probability	0	0	0.000001	0	0	0
Q-Stat lag 20	40.6	1587.4	2297.6	63.2	7907.4	36.8
Sum	-0.500519	148.9157	-639.8685	0.518312	658.19	0.09
Sum Sq. Dev.	1.252256	7.706646	64.28759	6.869452	7.348548	0.249884
Observations	500	500	500	500	500	499

Period from 15th of January 2008 to 5th of June 2018.

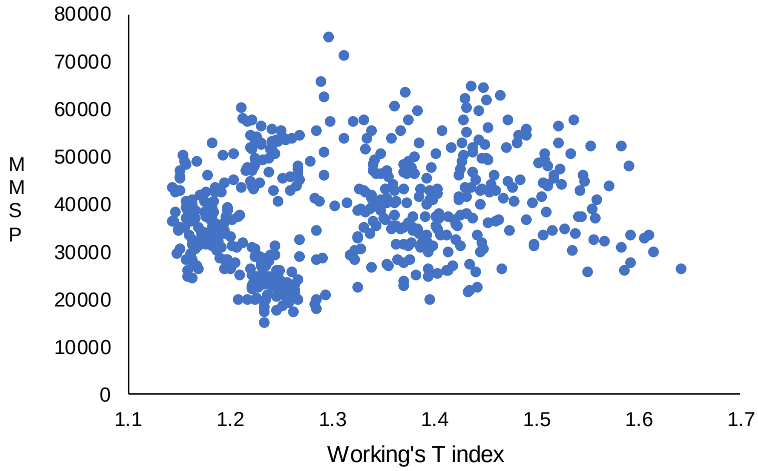
Table 2 displays stationary Phillips-Perron tests for all the variables considered, which show stationary to the usual levels of 1,5 and 10% respectively according to the Phillips-Perron test statistics. Working's T is the only variable non-stationary at 1 and 5%. Then to proceed with the causality analysis Working's T index is first differenced.

Table 2 Phillips- Perron t statistics for the variables of interest

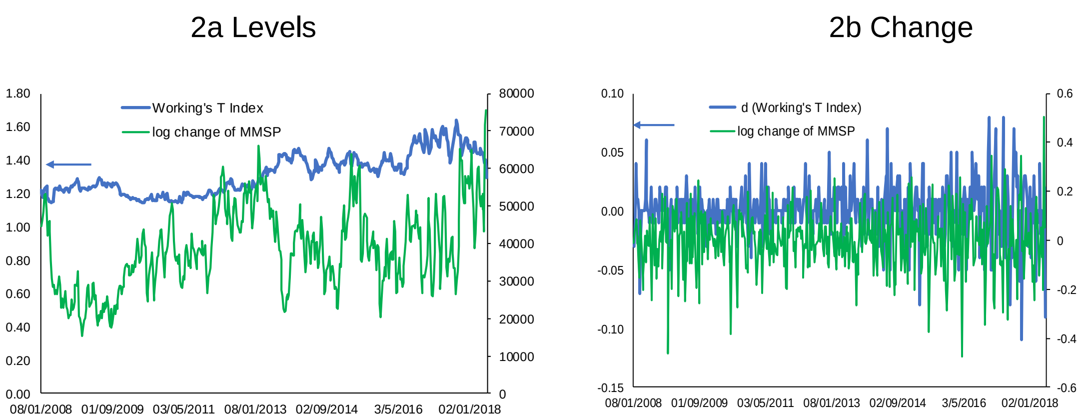
Phillips-Perron t-statistics	Log returns	Realised Volatility Rogers	Log Realised Volatility Rogers	Managed Money Spreading Positions	Working T Index	D(Working T Index)
Adjusted t-statistics	-24.6484300	-17.4022500	-16.4628000	-25.5215900	-3.1506940	-21.2416600

Stationary tests with a constant and trend.
Test critical values: 1% level, -3.98; 5% level, -3.42, 10% level -3.13%

Graph 1 Scatter plot of weekly levels of the speculative measures: MMSP and Working's T index from 15 Jan 2008 to 5 Jun 2018



Graph 2 Wheat futures prices speculative measures: managed money spreading positions (MMSP) and Working's T Index at weekly frequency



Source: Own computations based on data from U.S Commodity Futures Trading Comission (CFT).

The weekly log returns and managed money spreading positions of wheat futures prices exhibit similar level of excess kurtosis of 4.86 and 4.62 respectively, and a rather slight skewness; for the log returns a positive skewness equal to 0.46 and for the managed money spreading positions a negative skewness of -0.29. Whereas the weekly realised volatility of wheat futures prices shows a large excess kurtosis of 18.99 and positive skewness of 2.66, but the log of this realised volatility measure displays a level of excess kurtosis of 3.72 and positive skewness of 0.46. The Ljung-

Box test statistics for serial autocorrelation up to lag 20, do reject the null hypothesis of no serial autocorrelation at usual significance levels: 5 and 10 % (See Table 1).

Then the realised volatility measured by Rogers and Satchell´s (1991) formula of wheat futures prices and the weekly change of speculative positions do not come from a normal distribution, evidencing the presence of very fat tails for the case of the realised volatility of wheat futures prices in comparison with the change in speculative positions. These distribution features are similar to the stylized facts of financial literature about log returns and realised volatility proxies of stock and commodity markets.

Graph 1 displays the scatter plot portrays the weekly levels of both speculative measures showing a positive relationship between them, which is also illustrated by Graph 2a and 2b.

3.4 Methodology: Granger Causality and Vector Autoregressive Model (VAR)

Granger tests are used to indicate linear causality between two variables and are based on the bivariate Vector autoregressive model (VAR). For instance, the null hypothesis tests if $y1,_t$ *does not Granger causes* $y2,_t$, under the assumption that the error term $\boldsymbol{u_t}$ is a vector of stationary white noise processes. Hence, one can reject the null hypothesis if the estimated coefficients of $y1,_t$ are statistically different from zero. The Granger causality tests if, at time *t*, there is unidirectional causality from variable $y1,_t$ to $y2,_t$ or unidirectional causality from variable $y2,_t$ to variable $y1,_t$, or bidirectional causality from $y2,_t$ to $y1,_t$, and from variable $y1,_t$ to variable $y2,_t$, or if there is no Granger causality. The null hypothesis is tested with a F-statistic by comparing the estimated coefficients of the restricted model – where $y1,_t$ dynamics is explained only by pasts values of $y1,_t$, - with the ones of the unrestricted model - where $y1,_t$ dynamics is described by past values of $y1,_t$ and $y2,_t$. Andreasson et al. (2016, p.118).

For this empirical exercise, in order to estimate the effect of speculation (managed money spreading positions or Working's T index) on the log realised volatility or log returns of wheat futures prices. I estimate the following bivariate VAR which reduced form expresses the endogenous variables as function of p lagged endogenous variables

$$\boldsymbol{y_t} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1 y_{t-1}} + \boldsymbol{\beta_2 y_{t-2}} + \cdots + \boldsymbol{\beta_p y_{t-p}} + \boldsymbol{u_t} \qquad \textbf{(2)}$$

where both variables are endogenous

Based on the book chapter of Vector Autoregressive Models for Multivariate Time Series

For a bivariate VAR

$\boldsymbol{y_t}$ denotes the (2*1) column vector of two time series variables $\boldsymbol{y_t} = [y1,_t \ \ y2,_t]'$

The $y1,_t$ is either the weekly log realised volatility of wheat futures prices or log returns at time t; and $y2,_t$ is either the weekly log change of managed money spreading positions or Working's T index at time t.

$\boldsymbol{\beta_0}$ is 2*1 column vector of constants, and the $\boldsymbol{\beta_i}$ corresponds to each of the 2*2 matrix of parameter coefficients for VAR (p) where $i = 1, \dots, p$

$$\boldsymbol{\beta_0} = [\beta_1 , \beta_2]' \ ; \qquad \boldsymbol{\beta_i} = \begin{bmatrix} \beta_{11}{}^{i} , \beta_{12}{}^{i} \\ \beta_{21}{}^{i} , \beta_{22}{}^{i} \end{bmatrix}'$$

$\boldsymbol{u_t}$ is the 2*1 column vector of white noise process $\boldsymbol{u_t} = [u_{1t} , u_{2t}]'$

with the assumptions $E[\boldsymbol{u_t}] = 0$ for all t and $E[\boldsymbol{u_t}\,\boldsymbol{u_s}'] = \begin{Bmatrix} \Omega \ if \ t = s \\ 0 \ if \ t \neq s \end{Bmatrix}$

Ω is positive definite, and the errors are serially uncorrelated or independent.[38] The Ordinary Least Squares OLS estimators are consistent under the assumption of homoscedasticity and uncorrelated residuals.

[38] In order to guarantee the positive definiteness of the estimated covariance matrices and ensure positiveness of the realised volatility measure, nonnegativity restrictions on the parameters or the innovation process $\boldsymbol{u_t}$ must be imposed as suggested by Bollerslev.(as cited in Conrad and

My aim is to test if speculation were the cause or consequence of changes in the log realised volatility, and log returns of CBOT wheat futures prices over the sample period 2008-2018.

I follow the definition of speculation as investors holding positions in the expectation of earning a positive return in the commodity markets. By contrast, hedging implies investors taking positions in the commodity markets because they are necessary to the process of production and selling the commodities (see Alquist and Gervais, 2011).

The hypothesis is that there is an effect of the change of speculative measures impacting the log volatility of futures prices of wheat. It could come from the different interpretation that investors have about fundamentals, particularly over periods of higher uncertainty.

3.5 Empirical Results

All the time series presented are stationary according to the Philllips and Perron (1988) unit root test at the usual levels as reported previously on Table 2. Considering that data characteristics of the log returns of wheat futures prices and their respective log change of managed money spreading positions and the first difference of Working's T index exhibit serial autocorrelation according to the Ljung-Box test (see Table 1). I estimate the bivariate unrestricted VAR model with Ordinary Least Squares OLS applied to estimate each equation, following equation 2 from the Methodology section.

VAR (7)

$$\hat{\boldsymbol{y}}_{\boldsymbol{t}} = \hat{\boldsymbol{\beta}}_{\boldsymbol{0}} + \hat{\boldsymbol{\beta}}_{\boldsymbol{1}}\boldsymbol{y}_{\boldsymbol{t-1}} + \hat{\boldsymbol{\beta}}_{\boldsymbol{2}}\boldsymbol{y}_{\boldsymbol{t-2}} + \hat{\boldsymbol{\beta}}_{\boldsymbol{3}}\boldsymbol{y}_{\boldsymbol{t-3}} + \hat{\boldsymbol{\beta}}_{\boldsymbol{4}}\boldsymbol{y}_{\boldsymbol{t-4}} + \hat{\boldsymbol{\beta}}_{\boldsymbol{2}}\boldsymbol{y}_{\boldsymbol{t-5}} + \hat{\boldsymbol{\beta}}_{\boldsymbol{3}}\boldsymbol{y}_{\boldsymbol{t-6}} + \hat{\boldsymbol{\beta}}_{\boldsymbol{4}}\boldsymbol{y}_{\boldsymbol{t-7}} + \hat{\boldsymbol{u}}_{\boldsymbol{t}}$$

$$\hat{\boldsymbol{u}}_{\boldsymbol{t}/}\boldsymbol{y}_{\boldsymbol{t-1}},\boldsymbol{y}_{\boldsymbol{t-2}},\ldots,\boldsymbol{y}_{\boldsymbol{t-7}}\sim(\hat{\mu},\hat{\Omega})\ \textit{\textbf{innovation term, where }}\boldsymbol{\Omega}\textit{\textbf{ allows for heteroskedasticity and serial correlation}}$$

Karanasos, 2010). Alternatively, the econometric model can be estimated by using the logarithm of the realised volatility proxy.

The focus of this study is the impact of changes in speculation measured by the log change in managed money spreading positions and the Working's T-Index, on the log volatility of wheat futures over a weekly period that spans from January 15, 2008 to June 5, 2018. This empirical study, likewise, estimate the effect of the change of the same measures of speculation on the weekly futures log returns for the same period of time.

Following Singleton findings where the 13-week change of managed money positions and index investors show large and statistically significant effects on oil futures price returns; I choose 13 as the maximum lag order. It is important for correct statistical inference to find the lag order for the VAR model which minimizes information criteria such as the Akaike information criterion (AIC) and the Schwarz information criterion or the Bayesian information criterion (SC/BIC). The next step is testing for serial autocorrelation and heteroscedasticity in the residuals of the suggested VAR model, which I do by obtaining the Lagrange Multiplier (LM) test and the White heteroscedasticity test. Based on the residuals tests it is possible to select a higher order VAR always keeping in mind parsimony.

Table 3a shows that for the bivariate VAR of weekly realised volatility and the log change of managed money spreading positions, both the AIC and the BIC/SIC, lag 7 (-1.55) and lag 4 (-1.38) respectively are the ones which were selected by the information criteria. Given this mixed evidence further analysis is needed. In order to select the right VAR order for the weekly realised volatility measure I estimated both models VAR (4) and VAR (7) tested the residuals for serial correlation and heteroscedasticity with the Lagrange Multiplier test (LM) test and White heteroscedasticity test. The VAR model that satisfies the no autocorrelation and no heteroscedasticity condition is selected. In this case VAR (4) was the preferred model, which LM and White heteroscedasticity test have probabilities of 0.61 and 0.74 respectively, in which case the null hypotheses of no heteroscedasticity, and no serial autocorrelation are not rejected at usual significance levels. Thus, LM test suggests VAR (4) since the no serial correlation hypothesis is rejected for lag 7 at

10% of significance. Consequently, in this manner the bivariate VAR (4) is selected to account for serial autocorrelation and heteroscedasticity, all the VAR models also satisfy the stability condition with all the polynomial roots not lying outside the unit circle.

Table 3a Lag length selection of the Bivariate VAR of log realised volatility of wheat futures prices and the log change of the managed money spreading positions at weekly frequency

Lag	AIC	SC	HQ
4	-1.5416540	-1.386852*	-1.480842*
7	-1.550464*	-1.2924600	-1.4491110
13	-1.5238570	-1.0594490	-1.3414200

*indicates lag order selected by the criterion
AIC: Akaike information criterion.
SC: Schwarz information criterion also called the Bayesian information criterion.
HQ: Hannan-Quinn criterion.

Source: Own computations based on Datastream data and U.S Commodity Futures Trading Comission (CFT).

I follow the same lag length procedure for all the four bivariate VAR models estimations. The weekly log wheat futures returns and the log change in managed money spreading positions. Results for the VAR which satisfy the aforementioned criteria for the weekly log wheat futures returns and the change in managed money spreading positions are displayed on Table 3b, where according to the AIC the suggested model is VAR (4) because the value that minimizes the AIC criterion is -4.68. LM test registers a probability of 0.50 therefore the no autocorrelation hypothesis up to lag 4 is not rejected, however, it was needed to account for heteroscedasticity in the residuals when estimating the VAR model. It is expected to find mixed results when studying the predictability of commodity returns, due to the characteristic non-predictability nature of returns that has been found in the financial literature (See Table 3b).

Table 3b Lag length selection of the Bivariate VAR of log returns of wheat futures prices and the log change of the managed money spreading positions at weekly frequency

Lag	AIC	SC	HQ
0		-4.620503*	-4.630946*
4	-4.680391*		

*indicates lag order selected by the criterion
AIC: Akaike information criterion.
SC: Schwarz information criterion also called the Bayesian information criterion.
HQ: Hannan-Quinn criterion.

Source: Own computations based on Datastream data and U.S Commodity Futures Trading Comission (CFT).

Table 3c illustrates the Information Criteria to select the lag length for the bivariate VAR of the weekly log realised volatility and “excess speculation” of wheat, the latter measured by the Workings T index. The values which minimize each criterion: the AIC and the BIC/SIC, are for lag 7 (-4.83) and lag 4 (-4.66) respectively. The VAR (7) is selected because the autocorrelation and heteroscedasticity residual tests satisfy the no serial autocorrelation and no heteroscedasticity with probabilities of 0.52 and 0.19 respectively. In the case of the bivariate VAR of the weekly log returns and the “excess speculation” the AIC and BIC which minimize both criteria are for lag 5 (-8.02) and, lag 1 (-7.97) as displayed on Table 3d. Given these mixed results I estimate these bivariate VAR models and chose the lag length model in a similar fashion as when estimating the models using the alternative speculative measure. The VAR (7) was selected when accounting for heteroscedasticity and serial autocorrelation with probability values of 0.1021 and 0.2148 for the White heteroskedasticity and LM tests, respectively.

Table 3c Lag length selection of the Bivariate VAR of log realised volatility of wheat futures prices and the D(Working’s T index), at weekly frequency

Lag	AIC	SC	HQ
4	-4.8212220	-4.666177*	-4.760309*
7	-4.832158*	-4.5737500	-4.7306360
13	-4.7818290	-4.3166950	-4.5990910

*indicates lag order selected by the criterion
AIC: Akaike information criterion.
SC: Schwarz information criterion also called the Bayesian information criterion.
HQ: Hannan-Quinn criterion.

Source: Own computations based on Datastream data and U.S Commodity Futures Trading Comission (CFT).

Table 3d Lag length selection of the Bivariate VAR of log returns of wheat futures prices and the D (Working's T index), at weekly frequency

Lag	AIC	SC	HQ
1	-7.991714	-7.940114	-7.971444*
5	-8.015713*	-7.82651	-7.941387

*indicates lag order selected by the criterion
AIC: Akaike information criterion.
SC: Schwarz information criterion also called the Bayesian information criterion.
HQ: Hannan-Quinn criterion.

Source: Own computations based on DataStream data and U.S Commodity Futures Trading Comission (CFT).

In summary, the bivariate VAR models selected are the following, regarding the impact of alternative speculative proxy, the change managed money positions on log wheat realised volatility and log returns. The selected bivariate VAR models were the VAR (4) and VAR (4) for the log realised volatility and log return of wheat futures prices respectively, over the weekly horizon. When analysing the causality of the popular measure of the first difference "excess speculation" Working's T-Index on log volatility and log returns, VAR (7) and VAR (7) specifications were chosen.

I estimate all the bivariate VAR equations for the period spanning ten and a half years from 15/01/2008 to 05/06/2018. All the VAR models also satisfy the stability condition indicating that the VAR system is at least weakly stationary because all the eigenvalues of its characteristic roots are less than one in modulus, which mean are lying inside the unit circle.

Table 4a shows that the R^2 0.55 of the estimated equation between the log realised volatility of wheat and the log managed spreading positions indicates a good VAR fit between the persistent volatility process and the speculative measure, it also indicates a substantial predictability of the weekly wheat realised volatility. In contrast, the wheat log returns exhibit non-predictability by registering the R^2 0.033 on Table 4b. These results are in line with the stylized facts of returns and volatility process from the financial literature.

As displayed on Table 4a, log wheat realised volatility estimates are all statistically significant at 5 and 10 % levels. Evidencing that the majority of the volatility dynamics is explained by its own past, the estimates are higher for the first two lags and overall the weekly and two-week lags explain 29 and 20 % of the log volatility respectively. The weekly log change in managed money spreading positions has smaller estimates compared to the own past lags of volatility.

More interesting is the finding that for the whole sample period the two-week lag of the log change of managed money spreading positions is statistically significant at 5 % for the log realised volatility and the log returns, respectively, indicating a positive relationship with the weekly change of this measure of speculative positions and the log realised volatility of wheat, with an estimated value of 20.4%. With regards to the effect of speculation on log realised volatility, the four -week lag is also statistically significant at 5 % with an estimated coefficient of 24.4% displaying a similar relationship with respect to the speculative measure.

These results suggests that the second and fourth lags of the log change of managed money spread trading induce pressure on the weekly log realised volatility of wheat futures, a finding consistent with Singleton's (2014) hypothesis who claims that the growth of flows of index funds and the managed money spread trades influence oil futures prices, in particular excess returns, on the same direction, during a period of financial turmoil (See Table 4a and b).

The aforementioned evidence offers some reassurance about the impact of the change of speculative positions -measured by managed money spreading positions- on the log returns of wheat futures prices and the log of Rogers and Satchell´s realised volatility proxy, where the speculative impact is more likely to occur over the horizon of two and four weeks. Contrary to Singleton (2014) findings where for crude oil futures weekly and monthly return prices the impact comes from the three past months or the 13-week change of speculative positions. A plausible explanation that this author gives is that these changes have been influenced by their different perceptions about the economic environment or their perceptions about the heterogeneous beliefs of other investors about the fundamentals.

Table 4a Bivariate VAR (7) of log realised volatility of wheat futures prices and the log change of the managed money spreading positions at weekly frequency

	LNWHEATVOLROGERS	LNCHANGEMMSP
LNWHEATVOLROGERS(-1)	0.293907	-0.005996
	[6.65283]	[-0.28428]
LNWHEATVOLROGERS(-2)	0.205235	-0.006269
	[4.50177]	[-0.28799]
LNWHEATVOLROGERS(-3)	0.171071	-0.027261
	[3.77017]	[-1.25832]
LNWHEATVOLROGERS(-4)	0.199767	0.023868
	[4.54731]	[1.13792]
LNCHANGEMMSP(-1)	-0.116547	0.076
	[-1.24858]	[1.70526]
LNCHANGEMMSP(-2)	0.203792	-0.106105
	[2.13244]	[-2.32534]
LNCHANGEMMSP(-3)	0.01513	-0.079439
	[0.15721]	[-1.72868]
LNCHANGEMMSP(-4)	0.244301	-0.187412
	[2.53932]	[-4.07990]
C	-0.167362	-0.019386
	[-3.58916]	[-0.87072]
R-squared	0.558339	0.06459
Sum sq. resids	28.14168	6.415516
Log likelihood	7.798914	374.4749
Akaike AIC	0.004843	-1.473689
Schwarz SC	0.081172	-1.39736
Mean dependent	-1.282013	0.000718
S.D. dependent	0.35878	0.11771
Determinant resid covariance (dof adj.)		7.58E-04
Determinant resid covariance		7.30E-04
Log likelihood		383.4934
Akaike information criterion		-1.473764
Schwarz criterion		-1.321106

Source: Own computations based on Datastream data and U.S Commodity Futures Trading Comission (CFT).

Table 4b Bivariate VAR (4) of log returns of wheat futures prices and the log change of the managed money spreading positions at weekly frequency

	WHEATLOGRET	LNCHANGEMMSP
WHEATLOGRET(-1)	-0.10515	0.01436
	[-2.31675]	[0.13736]
WHEATLOGRET(-2)	-0.035415	0.073147
	[-0.77679]	[0.69657]
WHEATLOGRET(-3)	0.041873	0.168725
	[0.92393]	[1.61633]
WHEATLOGRET(-4)	0.068644	-0.056068
	[1.51098]	[-0.53582]
LNCHANGEMMSP(-1)	0.010826	0.07663
	[0.55818]	[1.71539]
LNCHANGEMMSP(-2)	-0.053267	-0.100726
	[-2.69835]	[-2.21526]
LNCHANGEMMSP(-3)	-0.004344	-0.068418
	[-0.21757]	[-1.48772]
LNCHANGEMMSP(-4)	0.011234	-0.185949
	[0.56338]	[-4.04872]
C	-0.0012	0.000921
	[-0.53585]	[0.17852]
R-squared	0.033664	0.065151
Adj. R-squared	0.01779	0.049794
Sum sq. resids	1.208553	6.411669
S.E. equation	0.049816	0.114742
F-statistic	2.120687	4.242475
Log likelihood	788.4602	374.6236
Akaike AIC	-3.142985	-1.474289
Schwarz SC	-3.066656	-1.39796
Mean dependent	-0.001139	0.000718
S.D. dependent	0.050265	0.11771
Determinant resid covariance (dof adj.)		3.25E-05
Determinant resid covariance		3.13E-05
Log likelihood		1164.322
Akaike information criterion		-4.622267
Schwarz criterion		-4.469609
Number of coefficients		18

Source: Own computations based on Datastream data and U.S Commodity Futures Trading Comission (CFT).

Nevertheless, with regard to the weekly wheat log returns this relationship between returns and the change in speculative positions -measured by the log change in managed money spreading positions- is negative and also statistically significant at the usual levels. The estimate for the second lag of the change in managed money spreading positions is -5.3 %. Whereas, for the weekly returns regressed on their own past lagged values, only the first lag estimate of -.10 % is statistically significant.

In contrast, for both bivariate VAR equations that consider either the log realised volatility or the log returns of wheat futures prices regressed onto the weakly log change in managed money spreading positions, this speculative measure exhibits a negative relationship with its own history that is statistically significant at the usual levels for lag 2 and 4; but the estimates of either the log realised volatility or log returns of wheat futures prices are not statistically significant (See Tables 4a and b).

When making the causal analysis using the first difference of the Working's T-Index as a measure of "excess speculation" different results are obtained. First, the causal link comes from the log realised volatility and log returns to "excess speculation". For the former, lag 2 of the log realised volatility are statistically significant at 1%, and their estimate values are -1.1 %. For the latter, lags 1, 3 and 4 of the log returns are statistically significant at 1%, with estimates of -6, -8 and -5 % respectively. (See Tables 5a and b). These results are in line with (Andreasson et.at.al, 2016) with respect to the strong linear causal relationship from log returns to excess speculation, overall, for agricultural commodities.

Table 5a Bivariate VAR (7) of log realised volatility of wheat futures prices and the D(Working's T index) at weekly frequency

	LNWHEATVOLROGERS	D(WORKINGSTINDEX)
LNWHEATVOLROGERS(-1)	0.281612	-0.002777
	[6.19895]	[-0.65636]
LNWHEATVOLROGERS(-2)	0.175318	-0.011004
	[3.83594]	[-2.58539]
LNWHEATVOLROGERS(-3)	0.148339	-0.00509
	[3.19860]	[-1.17853]
LNWHEATVOLROGERS(-4)	0.156225	0.006729
	[3.36420]	[1.55584]
LNWHEATVOLROGERS(-5)	-0.054857	0.006265
	[-1.18208]	[1.44954]
LNWHEATVOLROGERS(-6)	0.052424	0.000124
	[1.14557]	[0.02904]
LNWHEATVOLROGERS(-7)	0.119143	0.005597
	[2.69947]	[1.36181]
D(WORKINGSTINDEX(-1))	0.439046	0.032362
	[0.88983]	[0.70428]
D(WORKINGSTINDEX(-2))	0.055418	-0.026314
	[0.11196]	[-0.57084]
D(WORKINGSTINDEX(-3))	-0.710422	-0.088585
	[-1.44220]	[-1.93100]
D(WORKINGSTINDEX(-4))	0.373115	-0.102305
	[0.76312]	[-2.24680]
D(WORKINGSTINDEX(-5))	0.082705	-0.093908
	[0.16958]	[-2.06754]
D(WORKINGSTINDEX(-6))	0.550889	-0.022875
	[1.12491]	[-0.50156]
D(WORKINGSTINDEX(-7))	0.114559	-0.114077
	[0.23390]	[-2.50099]
C	-0.161543	0.000227
	[-3.43778]	[0.05183]
R-squared	0.570172	0.075205
F-statistic	45.19611	2.770714
Log likelihood	26.91255	1194.807
Akaike AIC	-0.048425	-4.795965
Schwarz SC	0.079577	-4.667963
Mean dependent	-1.288389	0.000285
S.D. dependent	0.349785	0.022208
Determinant resid covariance (dof adj.)		2.54E-05
Determinant resid covariance		2.39E-05
Log likelihood		1221.721
Akaike information criterion		-4.844393
Schwarz criterion		-4.588389

Source: Own computations based on Datastream data and U.S Commodity Futures Trading Comission (CFT).

Table 5b Bivariate VAR (7) of log returns of wheat futures prices and the D (Working's T index) at weekly frequency

	WHEATLOGRET	D(WORKINGSTINDEX)
WHEATLOGRET(-1)	-0.107582	-0.062638
	[-2.36659]	[-3.19412]
WHEATLOGRET(-2)	-0.033719	-0.019706
	[-0.73085]	[-0.99012]
WHEATLOGRET(-3)	0.035459	-0.082539
	[0.76765]	[-4.14213]
WHEATLOGRET(-4)	0.052668	-0.052913
	[1.12180]	[-2.61252]
WHEATLOGRET(-5)	-0.069944	0.006956
	[-1.49620]	[0.34493]
D(WORKINGSTINDEX(-1))	-0.142474	0.023743
	[-1.33294]	[0.51492]
D(WORKINGSTINDEX(-2))	-0.071465	-0.046465
	[-0.67505]	[-1.01740]
D(WORKINGSTINDEX(-3))	0.149482	-0.105679
	[1.42823]	[-2.34059]
D(WORKINGSTINDEX(-4))	0.021585	-0.112109
	[0.20467]	[-2.46414]
D(WORKINGSTINDEX(-5))	-0.147403	-0.09611
	[-1.41039]	[-2.13172]
C	-0.001398	3.34E-05
	[-0.62027]	[0.03434]
R-squared	0.032970	0.091913
Adj. R-squared	0.012948	0.073112
Sum sq. resids	1.205698	0.224379
S.E. equation	0.049963	0.021553
F-statistic	1.646728	4.888746
Log likelihood	784.8671	1200.192
Akaike AIC	-3.133065	-4.814542
Schwarz SC	-3.039486	-4.720963
Mean dependent	-0.001275	0.000142
S.D. dependent	0.050289	0.022387
Determinant resid covariance (dof adj.)		1.16E-06
Determinant resid covariance		1.11E-06
Log likelihood		1985.847
Akaike information criterion		-7.950797
Schwarz criterion		-7.76364

Source: Own computations based on Datastream data and U.S Commodity Futures Trading Comission (CFT).

It is relevant to mention that the findings mentioned above are confirmed with the corresponding pairwise causality tests displayed on Tables 6a to 6d. With probability 0.0345 pairwise causality test shows unidirectional linear causality from the proposed alternative speculative measured by the weekly log change in managed money spreading positions to the weekly wheat log realised volatility proxy (see Table 6a).

Likewise, Table 6b illustrates there is unidirectional linear causality from the weekly log managed money spreading positions to the weekly wheat log returns, since the test rejects the null hypothesis of no Granger causality with probability 0.0198.

In contrast, pairwise causality tests using the popular proxy of excess speculation and the weekly realised volatility measure and evidence unidirectional linear causality from the wheat log returns to the excess speculation measured by the first difference of Workings T index, as displayed by Table 6c with probability 0.0094. Similarly results show unidirectional linear causality from the wheat log realised volatility to the first difference of the excess speculation proxy, rejecting the null hypothesis with probability 0.0181 as illustrated at Table 6d.

Pairwise causality Tests

Sample: 1 500
Weekly frequency

Table 6 a Lags 2

Null Hypothesis:	Obs	F-Statistic	Prob.
LNCHANGEMMSP does not Granger Cause LNWHEATVOLROGERS	498	3.38953	0.0345**
LNWHEATVOLROGERS does not Granger Cause LNCHANGEMMSP		0.25879	0.7721

With probability 0.0345 pairwise causality test shows unidirectional linear causality from the alternative speculative measure to wheat realised volatility at 5 % of significance

Table 6 b Lags 2

Null Hypothesis:	F-Statistic	Prob.
LNCHANGEMMSP does not Granger Cause WHEATLOGRET	3.9515	0.0198**
WHEATLOGRET does not Granger Cause LNCHANGEMMSP	0.59098	0.5542

With probability 0.0198 pairwise causality test shows unidirectional linear causality from the alternative speculative measure to wheat log returns at 5 % of significance.

Table 6 c Lags 2

Null Hypothesis:	F-Statistic	Prob.
D(WORKINGSTINDEX) does not Granger Cause WHEATLOGRET	0.89822	0.408
WHEATLOGRET does not Granger Cause D(WORKINGSTINDEX)	4.71692	0.0094***

With probability 0.0094 pairwise causality test shows unidirectional linear causality from the wheat log returns to the excess speculation measured by the first differenced Workings T index at 1 % of significance.

Table 6 d Lags 4

Null Hypothesis:	Obs	F-Statistic	Prob.
D(WORKINGSTINDEX) does not Granger Cause LNWHEATVOLROGERS	495	0.48459	0.7471
LNWHEATVOLROGERS does not Granger Cause D(WORKINGSTINDEX)		3.00715	0.0181**

With probability 0.0181 pairwise causality test shows unidirectional linear causality from the wheat realised volatility to the first difference of the excess speculation proxy, at 5 % of signifance.

3.6 Conclusion

This study offers evidence on the impact of two different proxies of speculation on wheat futures log returns and their corresponding measure of log realised volatility on the VAR framework. The empirical results suggest that the choice of the speculative measure matters. The novelty of this empirical exercise is the use of managed money position as a measure of speculation in the context of linear Granger causality, it is important to acknowledge that Granger causality differs from economic (structural) causality. As stated above, some of the criticisms regarding the impact of speculation on the commodities futures prices has been focused on the fact that some speculative measures do not solely reflect diversification.

In this regard, managed money spreading positions represent a better proxy for speculation relative to other measures. The findings in this chapter indicate that there is linear causality coming from speculation on both log returns and wheat log realised volatility over the weekly horizon. These results support the side of the literature which found evidence regarding the impact of speculation on different commodity futures prices. For example, Robles, Torero and von Braun (2009) utilize weekly CIT data to run Granger causality tests between index positions and future returns.

On the other hand, when using the most popular measure of speculation (Wokings' T), the empirical results are in line with Andreasson, et. Al (2016) and Buyuksahin and Harris (2011) who find strong unidirectional linear causality from commodity returns to the measure of excess speculation, likewise one-way causality from log realised volatility to speculation. This ambiguity in results suggests that future research is required to address the impact of different speculative measures on commodity prices. The results may well vary if applied to different commodities and there is also scope to test for non-linear causality in these relationships.

Conclusion

One of the main differences of Chapter 1 relative to previous research is that none of the studies evaluate the forecasting power of speculative measures of agricultural commodities in forecasting commodities or a global measure of commodity prices for the monthly horizon, which according to my findings- rather than the MIDAS or monthly model specification - have proved to offer more accurate forecasts than the AR(1), particularly during the crisis period. Results which are confirmed by using Open Interest as an alternative speculative measure.

Besides the recursive estimation of the MIDAS models sometimes offers better forecasts relative to the benchmark rather than the rolling window estimation. The recursive estimation captures some forecasting power of financial variables, in particular of commodity currencies, which suggest that it is important the way MIDAS models are estimated. Previous studies such as Baumeister, Guérin, and Kilian (2014) estimated MIDAS models recursively, which main results suggest that the forecasts obtained in the mixed data framework do not consistently provide better forecasts of the real price of crude oil in U.S than the benchmark. What is more, another study did not find improvements of the forecasting accuracy using MIDAS models to forecast the US spot price of corn in comparison with the non-change forecast and AR(1) in the case of Etienne (2015).

My research could be naturally extended to study the forecasting accuracy of other speculative measures apart from the money managed spreading positions for agricultural commodities, such positions are also available for petroleum and its products, natural gas and metals. Similarly, there are other speculative metrics such as index funds, and multivariate MIDAS models or other different type of models. The forecasts can also include different time horizons beyond the monthly returns and also consider other commodity measures.

Chapter 2 findings demonstrate that the Implied Volatility (IV) measures of the Dow Jones-UBS Commodity Index and the US Stock Market (VIX) improved the R^2 of the estimated models, but according to in-sample results the IV if statistical significant it is a biased estimator of the daily realised volatility measured by the absolute returns and the two range-price estimators [Parkinson´s (1980) and, Rogers and Satchell´s (1991)]. As previously stated, one of the main results of my empirical exercise is that the Heterogenous Autoregressive HAR specifications can offer forecasts which are statistically significant better to the ones provide by usual benchmarks such as GARCH(1,1) and EGARCH(1,1) when comparing the Root Mean Squared Error (RMSE) metrics.

It is worth mentioning that in my empirical exercise was not possible to evaluate the forecasting performance of competing models in forecasting the daily range-price realised volatility estimators during the financial crisis of 2008 due to data availability.

In further extension, regarding the forecast of realised volatilities of commodities, the aforementioned range-price estimators could be compared with realised volatility measures from high frequency data such as the 5-min or 30-min absolute return or realised volatility and realised power. Ghysels, Synko, and Valkanov (2007) found that the realised power was the best predictor of conditional volatility in the MIDAS framework. Besides, other set of predictors could be included such as speculative measures; apart from the implied volatility of call options it is also available the implied volatility of put options for the commodity markets. In similar fashion to Fengping, Ke, and Langnan (2017) the realised volatility forecasts of the simplest version of the Heterogeneous Autoregressive model (HAR) could be evaluated relative to the forecast of more sophisticated HAR versions which not only account for volatility persistence but it also allows the predictors and coefficients to vary over time.

The final chapter (Chapter 3) has various originalities it takes an overview of my previous studies and contributes in studying the linear Granger causal relationship between -following Granger and Vector Autoregressive (VAR) methodology-, the Chicago Board of Trade Wheat weekly futures returns and the famous measure of excess speculation, the Working's T Index; but as a novelty it also studies this relationship with the weekly log realised volatility measured by the Rogers and

Satchell's range-price estimator and an alternative speculative measure (money managed spreading positions MMSP) inspired by Singleton's (2014) results.

In line with previous literature regarding causality of commodities futures returns and this measure of excess speculation my findings show the existence of linear causality from log wheat futures returns to excess speculation (See Andreasson, Bekiros, Khuonh Nguyen, and Uddin, 2016), also my results suggest a one-way causality from the log realised volatility to excess speculation. In contrast, when analysing the Granger causality between the wheat log returns and log realised volatility and the alternative measure of speculation -managed money spreading positions-, my findings demonstrate the presence of unidirectional linear causality from speculation to both log wheat returns and the log realised volatility proxy.

In this regard further research regarding commodity prices causality can be extended to other commodities and include other predictors for example macroeconomic ones that were used by Mo, Gupta, Li and Singh (2018) to find the drivers of commodity futures volatility. The results of my third Chapter suggest that further studies incorporate money managed spreading positions as a speculative measure, since money clients are looking to obtain diversification benefits it makes sense that this MMSP can better reflect a speculative measure, and also because as Singleton stated (2014) the MMSP impact commodity prices through risk premiums, which is also the case of index funds investments. One thing to consider is that managed money spreading positions are only publicly available from 2006.

Bibliography

1. Andersen, T.G., Bollerslev, T., Christoffersen, P.F., and Diebold, F.X. (2006) ‘Handbook of Economic Forecasting, Volume I, *Elsevier,* Chapter 15, pp. 779-865.

2. Andersen, T.G., Bollerslev, T., Diebold, F.X., and Labys, P. (2003) ‘Modeling and Forecasting Realised Volatility’, *Econometrica,* 71, pp. 529-626.

3. Andersen, T.G., Bollerslev, T., Meddahi, N. (2005) ‘Correcting the Errors: Volatility Forecast Evaluation Using High-Frequency Data and Realised Volatilities’, *Econometrica*, 73(1), pp. 279-296.

4. Andreasson, P., Bekiros, S., Khuonh Nguyen, D., and Uddin, G., S. (2016) ‘Impact of speculation and economic uncertainty on commodity markets’, *International Review of Financial Analysis* 42, pp. 115-127.

5. Alquist, R., and Gervais, O. (2011) ‘The Role of Financial Speculation in Driving the Price of Crude Oil’. *Bank of Canada, Discussion Paper* 2011(6), pp. 1-22.

6. Armesto, M. T., Engemann, K. M., and Owyang, M. T. (2010) ‘Forecasting with Mixed Frequencies’, *Federal Reserve Bank of St. Louis Review*, 92(6), 521-36.

7. Baumeister, C., Guérin, P., and Kilian, L. (2014) ‘Do High-Frequency Financial Data Help Forecast Oil Prices? The MIDAS Touch at Work’, *Bank of Canada, Working Paper 2014-11*, pp.1-39.

8. Blanchard, O., and Gali, J. (2010) ‘The macroeconomic effects of oil shocks: why are the 2000s so different from the 1970s?’, *in Jordi Gali and Mark Gertler (eds), International Dimensions of Monetary Policy, University of Chicago Press*, pp.1-50.

9. Beidas-Strom, S., and Pescatori, A. (2014) ‘Oil Price Volatility and the Role of Speculation’, *IMF Working paper*, pp. 1-34.

10. Béntes, R.S. (2015) ‘A comparative analysis of the predictive power of implied volatility indices and GARCH forecasted volatility’, *Elsevier*, pp. 1-8.

11. Bekiros, S.D., and Diks, C.G.H. (2008) ‘The relationship between crude oil spot and futures prices: Cointegration, linear and nonlinear causality’, *Energy Economics*, 30 (5), pp. 2673-2685.

12. Bekiros, S.D., and Diks, C.G.H. (2008) ‘The nonlinear dynamic relationship of exchange rates: Parametric and nonparametric causality testing’, *Energy Journal of Macroeconomics*, 30, pp. 1641-1650.

13. Büyüksahin, B., and Robe, M., A. (2014) ‘Speculators, commodities and cross-market linkages’, *Journal of International Money and Finance*, 42, pp. 38-70.

14. Christiansen, C., Schmeling, M., and Schrimpf, A. (2012) ‘A comprehensive look at financial volatility prediction by economic variables’, *Journal of Applied Econometrics*, 27, pp. 956-977.

15. Conrad, C., and Karanasos, M. (2010) ‘Negative Volatility Spillovers in the Unrestricted ECCC-GARCH MODEL, *Econometric Theory*, 26, pp. 838-862.

16. Corsi, F. (2009) ‘A simple Approximate Long-Memory Model of Realised Volatility’, *Journal of Financial Econometrics*, 7(2), pp. 174-196.

17. Chen, X., and Ghysels, E. (2011) ‘News-Good or Bad- and Its Impact on Volatility Predictions over Multiple Horizons’, *Oxford University Press, The Review of Financial Studies*, 24 (1), pp. 46-81.

18. Chiriac, R., and Voev, V. (2011) ‘Modelling and Forecasting Multivariate Realised Volatility’, *Journal of Applied Econometrics*, 26(6), *Themes in Macroeconomics and Finance*, pp. 922-947.

19. Chen, Y., Rogoff, K., and Rossi, B. (2010) ‘Can exchange rates forecast commodity prices?’, *Quarterly Journal of Economics*, 125, pp. 1145–1194.

20. Clements, M.P, and Galvão, B. (2008) ‘Macroeconomic Forecasting with Mixed Frequency Data: Forecasting the US output growth’, *Journal of Business & Economic Statistics*, 26(4), pp. 546-554.

21. Diebold, F. X. (2013) ‘Comparing Predictive Accuracy, Twenty Years Later: A Personal Perspective on the Use and Abuse of Diebold-Mariano Tests, *Journal of Business and Economic Statistics*, 7(2), pp. 174-196.

22. Etienne, X. L. (2015) ‘Financialization of Agricultural Commodity Markets: Do Financial Data Help to Forecast Agricultural Prices?’, *AAEA & WAEA Joint Annual Meeting, July 26-28, San Francisco, California 205124, Agricultural and Applied Economics Association; Western Agricultural Economics Association*, pp. 1-37.

23. Fattouh, B., Kilian, L. and Mahadeva L. (2012) ‘The Role of Speculation in Oil Markets: What Have We Learned So Far’, *Journal of Applied Econometrics*, 29, pp. 454-478.

24. Frankel, J. (2006) 'The effect of monetary policy on real commodity prices', *National Bureau of Economic Research Working Paper #12713.*

25. Frankel, J., and Rose, A., K. (2009) 'Determinants of Agricultural and Mineral Commodity Prices', *National Bureau of Economic Research Working Paper #12713*

26. Fengping T., Ke Y., and Langnan Ch. (2017) 'Realised Volatility forecasting of agricultural commodity futures using the HAR model with time-varying sparsity', *International Journal of Forecasting,* pp. 132-152.

27. Fong, W.M. and Kim, H.S. (2001) 'Modelling the Conditional volatility of commodity index futures as a regime switching process', *Journal of Applied Econometrics*, 16, pp. 133-166.

28. Gargano, A., and Timmermann, A. (2014) 'Forecasting commodity price indexes using macroeconomic and financial predictor', *International Journal of Forecasting*, 30, pp. 825–843.

29. Ghysels, E. (2015) 'MIDAS Matlab Toolbox', *Department of Economics, University of North Carolina*, pp. 1-56.

30. Ghysels, E., Rubia, A., and Valkanov, R. (2009) 'Multi-period forecasts of Volatility: Direct, Iterated and Mixed-Data Approaches', *EFA 2009 Bergen Meetings Paper, pp.* 1-34.

31. Ghysels, E., Santa Clara, P., and Valkanov, R. (2004) 'The MIDAS Touch: Mixed Data Sampling Regression Models', *UCLA*, pp.1-33.

32. Ghysels, E., Synko, A., and Valkanov, R. (2007) 'MIDAS regressions: further results and new directions', *Econometric Reviews*, 26(1), pp. 53-90.

33. Gospodinov, N., and Jamali, I. (2013) 'Monetary Policy Surprises, Positions of Traders,and Changes in Commodity Futures Prices', *Working Paper 2013-12*, pp.1-39.

34. Groen, J.J.J., and Pesenti, P.A. (2011) 'Commodity prices, commodity currencies, and global economic developments', *Economic Papers*, 440, pp. 1-35.

35. Goyal, A., and Welch, I. (2008) 'A comprehensive look at the empirical performance of equity premium prediction', *Review of Financial Studies*, 21, pp.1455–1508.

36. Goyal, A. (2010) 'Predictability of Stock Return Volatility from GARCH Models', *JEL classification*: C22, C5, pp. 1-44.

37. Haase, M. and M. Huss (2018) ‘Guilty speculators? Range-based conditional volatility in a cross-section of wheat futures’, *Journal of Commodity Markets*.

38. Hansen, P. R., and Lunde, A. (2011) ‘Forecasting Volatility using High Frequency Data’, *Oxford handbook of economic forecasting, Oxford University Press*, pp. 1-37.

39. Hansen, P. R., Huang Z., and Shek H. H. (2012) ‘Realised GARCH: A joint model for returns and realised measures of volatility’, *Journal of Applied Econometrics*, 27(6), pp. 877-906.

40. Huang, W., Huang, Z., and Matei, M. (2012) ‘Price Volatility Forecast for Agricultural Commodity Futures: The Role of High-Frequency Data’, *Romanian Journal for Economic Forecasting*, pp. 83-103.

41. Hamilton, J. D., and Wu, J. C. (2013) ‘Effects of index-fund investing on commodity futures prices’, *University of California at San Diego, Working paper*, pp. 1-42.

42. Hong, H., and Yogo, M. (2012) ‘What does futures market interest tell us about the macroeconomy and asset prices?’, *Journal of Financial Economics*, 105, pp. 473–490.

43. Ivanov, V., and Kilian, L. (2005) ‘A Practitioner’s Guide to Lag Order Selection for VAR Impulse Response Analysis’, *The Berkeley Electronic Press*, 9 (1), pp. 1-36.

44. Irwin, S.H., and Sanders, D.R. (2011) ‘Index Funds, Financialization, and Commodity Futures Markets’, *Applied Economic Perspectives and Policy*, 33 (1), (Spring 2011), pp. 1–31.

45. Irwin, S.H., and Sanders, D.R. (2012) ‘Testing the Masters Hypothesis in commodity futures markets’, *Energy Economics*, 34, pp. 256-269.

46. Kilian, L., and Thomas K. L. (2013) ‘Quantifying the Speculative Component in the Real Price of Oil: The Role of Global Oil Inventories’, *Journal of International Money and Finance*.

47. Kilian, L. (2014) ‘Oil Price Shocks: Causes and Consequences’, *Annual Review of Resource Economics*, 6, pp. 133-154.

48. Kroner, K.F., Kneafsey, D.P. and Claessens, S. (1993) ‘Forecasting Volatility in Commodity Markets’, *The World Bank, Policy Research Working Paper*,1226, pp. 1-28.

49. Liu, C., and Maheu, J. (2009) ‘Forecasting Realised Volatility: A Bayesian Model-Averaging Approach’, *Journal of Applied Econometrics,* 24, pp. 709-733.

50. Marcellino, M., Stock, J. and Watson, M. (2005) ‘A Comparison of Direct and Iterated Multistep AR Methods for Forecasting Macroeconomic Time Series’, *IGIER Working Paper No. 285*, pp. 1-31.

51. Marsilli, C. (2016) ‘LASSO Variable Selection in Predictive MIDAS Models’, *Banque de France, Document de travail n°520.*

52. Mo, D., Gupta, R., Li, B., and Singh, T. (2018) ‘The macroeconomic determinants of commodity futures volatility: Evidence from Chinese and Indian markets’, *Economic Modelling*, 70 (C), pp. 543-560.

53. Musunuru, N., Yu, M., and Larson A. (2013) ‘Forecasting Volatility of Returns for Corn using GARCH Models’, *The Texas Journal of Agriculture and Natural Resources*, 26, pp. 42-55.

54. Patton, A., J. (2011) ‘Volatility forecasting comparison using imperfect volatility proxies’, *Journal of Econometrics*, 160, pp. 246-256.

55. Poon, S-H., and Granger, C.W.J. (2003) ‘Forecasting Volatility in Financial Markets: A Review’, *Journal of Economic Literature*, 41(2), pp. 478-539.

56. Roache, S., K. (2012) ‘China's Impact on World Commodity Markets’, *IMF Working Paper,* 12 (115), pp. 1-24.

57. Robles, L., Torero, M., and Von Braun, J. (2009) ‘When speculation matters’, *International Food Policy Research Institute (IFPRI),* 57.

58. Shephard, N., and Sheppard K. (2010) ‘Realising the future: forecasting with high-frequency-based volatility (heavy models)’, *Journal of Applied Econometrics*, 25, pp. 197-231.

59. Silvennoinen, A., Thorp, S. (2013) ‘Financialization, crisis and commodity correlation dynamics’, *Journal of International Financial Markets, Institutions and Money,* 24 (issue C), pp. 42-65.

60. Singleton, K. J. (2010) ‘The 2008 Boom/Bust in Oil Prices’, *Graduate School of Business, Stanford University*, pp. 1-26.

61. Singleton, K. J. (2014) ‘The 2008 Boom/Bust in Oil Prices’, *Management Science, 60 (2) , pp. 300-318.*

62. Varadi, V. (2013) ‘Determinants of volatile commodity prices’. *ICRIER*. DOI: http://ssrn.com/abstract=2201080

63. ‘Vector Autoregressive Models for Multivariate Time Series’, Book Chapter published in Modelling Financial Time Series with S-PLUS, pp. 385-429

64. Viteva, S., Veld-Merkoulova, Y. V., and Campbell, K. (2014) ‘The forecasting accuracy of implied volatility from ECX carbon options’, *Energy Economics*, 45, pp. 475-484

65. Wang, F., and Liu, C. (2008) ‘Determinants of the volatility of futures markets price returns: The case of Chinese wheat futures’, *2008 International Conference on Management Science and Engineering 15th Annual Conference Proceedings*, Long Beach, CA, 2008, pp. 693-698.