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Volatility Spillover between Water, Food And Energy

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Abstract

Water, food and energy are strongly interconnected. In this study we address this issue taking the lens of financial concerns to investigate the WFE relationship. Specifically, the aim of our paper is to analyze the volatility spillovers between indexes representing the financial component of WFE nexus. We use a multivariate GARCH model with daily data from November 2001 to May 2013. Water is proxy by equity index that represents the performance of the industry involved in water business both at global and local level. For the food and energy sectors we use two sub-indexes of S&P GS-Commodity Index. Our results highlight the existences of a financial nexus between WFE that is particular exacerbated during 2008 crisis. Evidence therefore suggests the need to better investigate the policy options that can be used to reduce price volatility in a framework of a rising relevance of water issues within the nexus.

Keywords: water, food, energy, nexus, M-GARCH, volatility spillover

JEL codes: Q02, Q25, Q11, G15, C58

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1. Introduction

Water, food and energy (WFE) are strongly interconnected: each depends on the other for a lot of aspects, spanning from guaranteeing access to services, to environmental, social and ethical impact issues, as well as economic relations.

The development, use, and waste generated by demand for these resources drive global changes and create concerns for resource scarcity. To date, a new approach to the concept of sustainable development is emerging and a joint analysis of these three areas is needed. “Demand for water, food and energy is expected to rise by 30-50% in the next two decades, while economic disparities incentive short-term responses in production and consumption that undermine long-term sustainability. Shortages could cause social and political instability, geopolitical conflict and irreparable environmental damages. Any strategy that focuses on one part of the WFE relationship without considering its interconnections risks serious unintended consequences” (World Economic Forum, 2011).

In the last years international organizations have organized several conferences to raise awareness of the WFE nexus (IISD 2011, footnote p.6) and some studies have addressed this issue trying to provide a theoretical integrated view aimed at understanding how to tackle these complex relationships when designing policies and taking appropriate actions (Bazilian et al. 2011, Elobeid et al. 2013, Howells et al. 2013). These studies have analyzed the technical connection that exists between the three elements in order to highlight the need for a joint policy aimed at ensuring a sustainable development.

From an economic point of view, there are still very few analyses that utilize empirical approaches to validate recent theoretical literature (Peterson et al. 2014, Curmi et al. 2013). This area of study is clearly wide and an economic analysis of the link aimed at understanding the interactions and correlations on a global scale is still needed.

An empirical analysis on the nexus should need economic data which are not available for water, since it is not treated as a commodity, and consequently there are no specific information to economically measure the water at global level. This means that it is very difficult to give an economic dimension to water and every analysis of economic nature must be addressed by narrowing the field according to a specific approach. In this study we therefore address this issue taking a specific lens to investigate the WFE relationship, i.e. the lens of financial concerns.

Indeed, the financial theory states that the more the financial components are correlated the greater is the possibility that shocks propagate between sectors. Therefore, taking the financial perspective has the important advantage to highlight the strength of these relations and their dynamics to better understand if and how shocks are transmitted from one sector to the others.

Within this framework, the aim of our paper is to empirically analyze the correlation and the volatility spillovers between variables representing the financial component of water, food and energy. A good understanding of the origins and drivers of volatility and cross market correlation is crucial because it can help policy makers in taking the proper measures to mitigate the potential correlations across the use of these resources which may create future undesirable shocks to the world and domestic economy.

Taking into account that water, food and energy are inextricably interlinked around the world, the nexus approach needs to be addressed on a global scale, but at the same time we also know that actions must be locals. Therefore, considering that different areas in the World have different degree of financial market integration, we focus both on global scale and on different geographical areas such as Europe, North America, Latin America and Asia.

To perform the analysis, we use a multivariate GARCH model with Dynamic Conditional Correlation (Engle, 1982, 2002; Engle and Kroner, 1995), which appears the most proper econometric methodology to study the shock transmissions, the volatility spillover effects and the dynamics of conditional volatility between markets.

Water is proxy by equity indexes provided by Datastream that represent the performance of the industry involved in water business both at global and local level, such as World overall, Europe, North America, Latin America and Asia.

For the food and energy sectors we use two sub-indexes of S&P GS-Commodity Index, respectively the S&P Agriculture-Livestock Index and the S&P Energy Index. The rationale for the choice of these two variables is that these commodity indexes have gained increasing importance within financial market by commodity index traders and therefore can be viewed as a financial asset that can be appropriately analyzed in relation with water index. Indeed, as well as for water index, such commodity indexes constitute a benchmark for a large amount of financial products with a real-asset exposure; the commodity index swaps, exchange traded funds (ETFs) and exchange traded notes (ETNs). Typically, hedge funds, pension funds, and other large institutions purchase these financial instruments relating to agricultural commodities with the aim of diversifying their portfolios.

We use daily data spanning from November 2001 to May 2013. The timeframe covers the 2008 economic and financial crises and allows us to assess whether it influenced the relationship between the sectors.

The novelty in this work is twofold. Firstly, the paper focuses on a topic of great relevance from an economic, environmental and ethical perspective, as recently outlined by many international organizations. The complex interactions and policy implications that consider all three sectors together need more work in order to effectively support decision-making. To the authors' knowledge no previous study has investigated the WFE relationship using a financial lens to understand economic spillover between the three sectors. Secondly, it performs the first econometric analysis of the financial relationship among these three sectors using a Dynamic Conditional Correlation model that permits studying in a dynamic framework the evolution of the indexes relationships and detect times of high and low correlation between the sectors.

The paper is organized as follows: Section 2 focuses on issues related to the WFE nexus, Section 3 presents the empirical framework, Section 4 presents the data, Section 5 reports the results, Section 6 discusses the main conclusions.

2. The water- food-energy nexus

Population growth, changes in lifestyles, increasing prosperity are putting rising pressures on resources. According to international organizations – such as the FAO, the International Food Policy Research Institute IFRI and the International Energy Agency IEA – by 2030 the demand for food, energy and water is expected to rise by 30-50%.

Resources are scarce and shortages could impact on communities and cause social and political instability, geopolitical conflict, environmental degradation. Consequently, in order to satisfy such an increasing demand many efficiency improvements for both development and implementation need to be achieved: new sources for food, changes in water use, more efficient mix of energy production systems.

Improvements require not only research and developments investments and funds, but also an integrated approach since water, food and energy are strongly interrelated. Indeed, agriculture and food both require large amount of water and energy in all the production stages (Ercin and Hoekstra, 2014); energy production needs water as well as bio-resources; water extraction and distribution requires energy. Bazilian et al. (2011) clearly and exhaustively identify the descriptive elements of the WEF nexus. Among them:

- many billions of people are without access to any or all the three areas (quantity or quality or both. Lack of access to modern fuels or technologies for cooking/heating; lack of access to safe water; no improved sanitation; people chronically hungry due to extreme poverty; lack of food security);
- all three areas have rapidly growing global demand;

- all have resources constraints;
- all have different regional availability and variations in supply and demand;
- all have strong interdependencies with climate change and the environment.

Given those interrelations, any improvement strategy that focuses on water, food and energy without considering their nexus risks unintended negative consequences. For example, the use of biofuel reduces vehicle emissions, but at the same time, it may impact worldwide availability of food and lead to higher agricultural prices (Peri and Baldi, 2010). Likewise, shale gas extraction can reduce the use of fossil fuels and is cleaner-burning than oil and coal; nevertheless, hydraulic fracturing requires large amount of water and this reduces the availability of water for other uses. Moreover, the fluid injected into the subsurface contains chemical additives that can contaminate surrounding areas.

Those are clearly trade-offs that policy makers have to think about when assessing planning for investments, actions and policies. The water, food and energy nexus needs global governance and integrated response strategies.

3. The Dynamic Conditional Correlation approach

In order to allow for interdependencies of volatilities across WFE markets we apply a multivariate GARCH (MGARCH) model with the conditional variance assumed to be VARMA (Ling and McAler, 2003) and with the dynamic conditional correlation (DCC) specification of Engle (2002) for the analysis of dynamic covariances and correlation across markets. This approach has been shown to be more useful when studying volatility spillover mechanisms than univariate models that do not allow for a cross-market volatility spillover effect which is likely to occur with increasing market integration. One of the main advantages of this model is that it permits exploring the shock transmissions, the volatility spillover effects and the dynamics of conditional volatility between series. Moreover this model provides meaningful estimates of the unknown parameters with less computational complication of other multivariate specifications (Hammoudeh et al. 2009, Tse and Tsui 2002).

In MGARCH approach we model the mean equation, the variance equation and the time relationships as follows.

We use a VAR system in the mean equation to allow for autocorrelation and cross correlation in the returns. To let a shock in one index to affect the variance of the others in the system we model the variance equation to be vector autoregressive moving average-GARCH (Ling and McAleer, 2003).

Finally, to increase model flexibility for studying over time evolution of the indexes relationships we use dynamic conditional correlation (DCC) model of Engle (2002).

In the multivariate GARCH we use the following mean equation specification (Silvennoinen and Teräsvirta, 2008):

$$R_{i,t} = \alpha_i + \sum_{j=1}^{n} b_{ij} R_{j,t-1} + \varepsilon_{i,t} \tag{1}$$

$$\varepsilon_{i,t} = h_{i,t}^{\frac{1}{2}} v_{i,t} \tag{2}$$

where: i is index of the investigated sectors; n is the total number of sectors (for WFE nexus n=3); $R_{i,t}$ is the return calculated by first log difference of ith price index at time t; $\varepsilon_{i,t}$ is a random error term of the mean equation with conditional variance $h_{i,t}$; and $v_{i,t}$ is the innovation that is distributed as an i.i.d random vector.

Information criteria are used for the lag length selection for VAR in the mean equation. Based on AIC information criteria, in all the models tested the number of lag selected for the VAR systems is equal to one.

The variance term is specified as follows (Ling and McAleer, 2003):

$$h_{i,t} = c_j + \sum_{j=1}^{n} \alpha_{ij} \varepsilon_{j,t-1}^{2} + \sum_{j=1}^{n} \beta_{ij} h_{j,t-1} \tag{3}$$

Equation (3) is a generalization of the Bollerslev (1990) specification which accommodate for interdependencies of volatility across indexes. $h_{i,t}$ is the conditional variance at time t, $h_{j,t-1}$ represent the own past variance when j=i while, when j≠i it denotes past conditional variance of the indexes in the system.

$\sum_{j=1}^{n} \alpha_{ij} \varepsilon_{j,t-1}^{2}$ is the short run persistence (ARCH effects) while the long run persistence or GARCH effects is $\sum_{j=1}^{n} \beta_{ij} h_{j,t-1}$.

The analysis of dynamic covariances and correlation across markets is carried out using dynamic conditional correlation (DCC) by Engle (2002) that is a generalized version of the constant conditional correlation (CCC) model by Bollerslev (1990). This representation is one of the most widely-used in financial analysis (see Bauwens et al. 2006 for a review) and more recently in energy finance (Lanza et al., 2006; Sadorsky, 2012; Hammoudeh et al. 2013).

The specification of Engle's DCC model is as follows:

$$H_t = D_t R_t D_t \tag{4}$$

Where H_t is the conditional covariance matrix; D_t is a n x n diagonal matrix of conditional, time varying, standardized residuals estimated in a first step by univariate GARCH models; R_t is the n x n time varying correlation matrix with the following form[1]:

$$R_t = diag\left(q_{11t}^{-1/2},...,q_{nnt}^{-1/2}\right)Q_t diag\left(q_{11t}^{-1/2},...,q_{nnt}^{-1/2}\right) \tag{5}$$

Conditionally to the estimated D_t in a second step the correlation component Q_t , that is a weighted average of a positive definite and a positive semidefinite matrix, is estimated with the following equation:

$$Q_t = (1-\theta_1-\theta_2)Q_0 + \theta_1\varepsilon_{t-1}\varepsilon_{t-1}' + \theta_2 Q_{t-1} \tag{6}$$

where Q_0 is the unconditional correlation matrix of the standardized residual epsilon, θ_1 and θ_2 are the parameters that respectively indicate the impact of past shocks on current conditional correlation and the impact of the past correlations. The model is mean reverting as long as $\theta_1 + \theta_2 < 1$. The dynamic conditional correlation coefficient $\rho_{I,j,t}$, that are typical elements of Q_t, are calculated as in equation 7:

$$\rho_{i,j,t} = \frac{q_{i,j,t}}{\sqrt{q_{i,i,t}q_{j,j,t}}} \tag{7}$$

In the empirical application the model is estimated using quasi maximum likelihood estimator (QMLE) by BFGS algorithm. t statistics are calculated using robust estimate of the covariance matrix.

For the specific purpose of this study we specify a MGARCH with n=3.

[1] In Constant Conditional Correlation models R_t=R, with R time invariant.

4. Data

We use daily data spanning from November 2001 to May 2013 obtained from Datastream. For water component we use equity indexes that provide liquid and tradable exposure to the main companies from around the world that are involved in the water related businesses. Data on geographic water equity indexes are from Datastream too and represent the performance of the major industry involved to water sector for a given area (Maxwell 2009, 2013). Specifically the data used are for Europe, North America, Latin America, and Asia. For agriculture and energy sectors we used two sub-indexes of S&P GS-Commodity Index. These indexes are a proxy for the level of nearby commodity prices, for Agriculture-Livestock and Energy. Specifically the S&P GSCI Agriculture and Livestock Index comprises the following index components: Wheat, Corn, Soybeans, Cotton, Sugar, Coffee, Cocoa, Feeder Cattle, Live Cattle, and Lean Hogs[2]. While the S&P GSCI Energy Index comprises WTI Crude Oil, Brent Crude Oil, RBOB Gas, Heating Oil, Gas Oil and Natural Gas. Both the indexes are calculated primarily on a world production weighted basis, and comprise the principal physical commodities that are the subject of active, liquid futures markets . The weight of each commodity in the index is determined by the average quantity of production as per the last five years of available data. All indexes are "capitalization-weighted", that is the components are weighted according to the total market-value of their outstanding shares.

Figure 1 shows trend for Water index for World and for the other four areas considered. All the series show an increasing trend until the end of 2007 then slipped down to be followed by a new growth but distinct differences are present between the areas.

[insert figure 1]

Asia index has more than quintupled during the first six years, but then its value drops during the financial crisis. Afterwards the index grows again very intensely until it reaches the 2007-level. Energy and agriculture follow similar trends although they have become fairly distinguished in recent years. North America water index increases considerably crisis whereas Europe index shows poor performances after 2011. Figure 2 reports Agriculture and Energy indexes trends. The graphical representation suggests that the two series follow an increasing trend until the crisis, both reaching unprecedented heights in the middle of 2008 and subsequently still declining with remarkable speed.

[insert figure 2]

[2] As states the Waterfootprint organization (www.waterfootprint.org) animal products generally have a larger water footprint than crop products. That's why we utilize an index comprising both agriculture and livestock products instead of only agriculture products.

After this period indexes level grew again at different rate but only agricultural has reached and exceeded past levels.

Table 1 shows the descriptive statistics of continuously compounded daily returns for each series.

[insert table 1]

The t-statistics indicate that the mean is statistically significant only for Asia Water index whereas the other indices' means are statistically insignificant from zero. Noticeably, Water indexes returns display a stronger amount of kurtosis than Agricultural and Energy indexes. Skewness is negative for all the indexes, but Asia. The higher the kurtosis coefficient is above the normal level, the more likely future returns will be either extremely large or extremely small. This fact suggests the need to account for the presence of volatility in our models confirming the idea of using an Autoregressive Conditional Heteroskedasticity (ARCH) approach.

5. Empirical results and comments

We first test for the existence of ARCH effects in the series and then we proceed with the estimate of a multivariate GARCH model, with the mean equation modelled as a VAR system. Table 2 reports results of multivariate GARCH estimate for all the investigated areas.

[insert table 2]

The estimates of these models can provide measures of the significance of the short-run persistence, ARCH effects of past shocks, own ($a_{i,i}$) and among sectors ($a_{i,j}$) and the long-run persistence, GARCH effects of own ($b_{i,i}$) and spillover ($b_{i,j}$) past volatilities. In the table coefficient $a_{1,3}$ represents the short term volatility spillover from Energy (3) to Water (1) while $b_{2,3}$ represents the long term volatility spillover from Energy (3) to Agricultural (2).

The first part of the table shows the mean equations estimates and the second the variance equation estimates. Overall, most of the coefficients are significant for World and for the others geographic areas. In the following we will focus our discussion only on the significant terms.

In variance equation ARCH effects are mostly significant. Own conditional effects ($a_{i,i}$) are always positive and bigger than cross effects as expected, with Water coefficient (ranging from 0.055 to 0.074) that shows the strongest shocks dependence. Agriculture and Energy markets highlight a smaller own dependence (from 0.035 to 0.042) and a very similar own news sensitivity between areas.

Inter sector short run/shock spillovers of the three indexes show different patterns between geographical areas and between each other. Agriculture to Water coefficient ($a_{1,2}$) is significant only in World equation whereas no substantial effect is present at local level. Positive spillover effects are present in particular in North and Latin America. It is interesting to note that shocks from Water to Agriculture and from Agriculture to Energy are always negative, suggesting that water volatility tone down agricultural volatility and then energy.

Examining market interactions in terms of the conditional second moment can provide better insight into the dynamic price relationships of markets. Long term persistence expressed by GARCH coefficients (b_{ii}) is still always present with all the coefficients significant. For each i, the estimated b_{ii} values are bigger than their respective estimated a_{ii} values, ranging from 0.802 to 0.957. This suggests that past own volatilities are more important in predicting future volatility than past shocks or news in all three sectors. There is also evidence of cross volatility effects between all the three sectors with many b_{ij} coefficients significant at the 1% or 10% level. Also in this case World and Americas show the best performance in statistical terms.

Specifically, cross volatility in Water-Agriculture is always positive in both directions of causality except for Asia. Instead, Water-Energy links show negative cross-GARCH coefficients implying therefore a volatility cooling effect between these sectors. For what that concerns the relation Agriculture to Energy and *vice versa*, still the results show past volatility spillover for the most of the areas. Specifically there is a negative cross-volatility from Energy to Agriculture and from Energy to Water although there is also a volatility cooling effect from Water to Energy.

The Ljung-Box diagnostic test is reported in Table 3. This test tests the null hypothesis that there is no autocorrelation up to order 12 and 20 for standardized residuals; the null hypothesis up to order 12 and 20 are always not rejected.

[insert table 3]

Overall results confirm that models perform statistically well. ARCH and GARCH coefficients highlight that even considering the entire period, volatility spillover exists between water, agricultural and energy sector; this result is itself relevant since it confirms the existence of a nexus in the short and long term.

Nevertheless, table 2 reports results considering very long period which includes numerous events and circumstances. To better fit with the purpose of this analysis we also report the graphs of the time varying dynamic conditional correlations (figure 3) that plot the time series for each of the geographical area studied for the following pairs of series: agriculture/energy, water/agriculture and water/energy. These figures show how effects evolve over time and what is the relationship between price indexes in function of both the history of variance (volatility) that each series as undergone and correlation between them. Overall, the dynamic conditional correlation is positive. At World level a very strong break is evident in the middle of 2008, when the economic and financial crises occurred. After this moment, a strong upwards pattern is evident for each pair of correlations and for the most of geographical areas.

[insert figure 3]

Agriculture and Energy relationship evolve with a similar pattern among the different areas investigated and shows the highest levels of correlation in Asia and North America.

Dynamics of Water-Energy and Water-Agriculture correlation show a similar trend too, highlighting in some case the effect of the crisis on the volatility transmission. Specifically Water and Energy show a very similar dynamics between Europe and Latin America and between North America and Asia. Similar distinction is outlined by the dynamic conditional correlation between Water and Agriculture. In Europe and Latin America both the DCCs sharply increased after the global economic downturn exceeding level 0.5, whereas this evidence becomes less noticeable in North America and Asia where correlations reach level around 0.3 and 0.2 respectively.

When analyzing the World as a whole, the differences in the lines that show the DCCs are much less, and this strengthens the idea that the water issue is much more substantial in a global perspective. After the crisis a strong upwards pattern is evident for each pair of correlation. Specifically, in few weeks the conditional correlation between water and energy jumps from -0.06 up to 0.60; similarly, the conditional correlation between water and agriculture increases from -0.03 to 0.59. Interestingly, before the financial crisis, the correlation between agriculture and energy is always stronger than the correlation of the two variables with water. Moreover, the water and energy relationship shows negative values only in few and short windows. Conversely, after the global economic downturn this evidence becomes unclear since in many periods the dynamic conditional correlation between water and energy and water and agriculture are higher than the correlations between agriculture and energy. This highlights the rising relevance of water issues within the nexus.

In Figure 4 we synthesize all the previous information by constructing a graph that tries to express, for each of geographical area, the nexus between water energy and food. Specifically, for all the investigated area the graph describes the mean value of the three dynamic conditional correlation (agriculture-energy, water-agriculture and water-energy).

[insert figure 4]

During the first period analyzed, from the end of November till the half of September 2008, the nexus between water, agriculture and energy moves on the same level for all the investigated areas with a mean DCC ranging from 0.11 to 0.16; in the subsequent period, all the values more than doubled reaching a mean level of 0.42 at a world scale with peaks greater than 0.6. Also in this case the World line almost always shows the highest correlations. These results are in line with recent economic literature (e.g., Buyuksahin, et al., 2010; Silvennoinen and Thorp, 2010; Tang and Xiong, 2010; Daskalaki and Skiadopoulos, 2011) that provides evidence that commodity returns and stock returns' correlation has gone up substantially during the recent financial crisis, and this despite the traditional negative correlation between commodity and equity returns documented by Greer (2000), Gorton and Rouwenhorst (2006), and Erb and Harvey (2006).

The huge amount of money invested by index trader in commodity markets, especially during and after the 2008 financial crisis, has created a new link between commodities and stock market and so, as outlined in our empirical exercise, also between agriculture, energy and water volatility.

These results are in line with King and Wadhwani (1990), that argue that the strength of international market links depends mainly on volatility, with stronger links in periods of high volatility and weaker correlation between price changes when volatility declines. The new global scenario, characterized by even more volatile markets, and the rising importance of these resources for humanity, highlight the relevance of a policy framework that accounts for the new concept of sustainable development, also considering the relevance of both technical and economic nexus between water, food and energy.

6. Conclusion

The new lines upon which is based the concept of sustainable development aim to analyze jointly water, energy and food. In this context, policy makers must operate by selecting those policy instruments acted to maintain a balance between the three components in order to avoid unwanted and distorted results.

Indeed, a policy that gives priority to the support of energy development will be reflected in a decline in the availability of water for other uses (e.g. agricultural) with a consequent increase in the prices of agricultural commodities and an increase in costs for water and sanitizing. This would result in higher costs for the community. Similarly, a policy based on priority support to agriculture and devoting the major water resources to this primary sector may cause competition for human use and for energy products with a consequent increase in the prices of final products.

In a context where global economies and sectors are strongly connected, forecast of population growth are impressive, and globalization has reduced the spatial dimension of trade, it is useful to identify pattern of sustainable development able to maintain the balance between these three areas adopting policy instrument in order to avoid price shock transmission between the three sectors. Within this framework political, economic and technical tools have to be arranged to help policy makers to develop the proper strategies for a sustainable development based on the WFE nexus.

Adopting an economic perspective there are different ways that can be taken into account in order to provide support to policy makers and to monitor these trends. In this paper, we make a small step in this direction by using the lens of financial perspective and performing the analysis of the dynamics of the three markets for different geographical area. The financial dimension of agriculture, energy and water as mentioned before, can be seen as a barometer to monitor the balance of the relations between WFE. Specifically we used two sub-indexes of S&P GS-Commodity Index for Agriculture-Livestock and Energy, while for Water the data are from Datastream and represent the performance of the major industry involved to water sector for a given area: Europe, North America, Latin America, Asia and World.

The analysis is carried out following two steps. Firstly, we apply a Multivariate GARCH model to test and quantify the presence of spillover effects between Water, Agricultural and Energy price change. ARCH and GARCH coefficients highlight that volatility spillovers exist between the three sectors and this result is itself relevant since it confirms the existence of a nexus in all the investigated area and at a world level in the short and long term.

Secondly, the Engle (2002) DCC specification of the M-GARCH framework allowed us also to track the trend of the relationships between variables by the plot of the time varying dynamic conditional correlation for each pair of series and for each geographical area. At World level the plot clearly shows that, after a period of low and slightly variable DCC, a very strong break took place during the economic crisis in September 2008. After this break, the dynamic conditional correlation (water-energy, water-agriculture, agriculture-energy) is much stronger in respect to the previous period, even if during the latest observation the level of correlation seems to revert to the level before the break.

Our results highlight the existences of a financial nexus between WFE that is particular exacerbated during finance turbulence, especially in Europe and Latin America. Evidence therefore suggests the need to better investigate the policy options that can be used to reduce price volatility in a framework of a rising relevance of water issues within the nexus. Moreover, these changes in conditional correlation have profound implications for a wide range of issues such as commodity producers, hedging strategies, speculators investment strategies and for the food and energy policies of many countries.

The growing demand of primary commodities like water, food and energy, the technical linkage between them and associated with their production use and consumption had stimulated international organization and academic researcher to move through a new concept of sustainable development. In this sense, the three sectors have to be planned jointly with the aim to develop response strategies within and across sectors, remembering that water is the common element that links these three areas that are fundamental for economic growth and human security. At a global or macro scale, economic literature has not yet investigated this topic in a nexus framework. Unfortunately, at this time both public and private financial institutions lack adequate analytical frameworks to value nexus issues. In this paper we try to fill this gap by following a financial approach as a lens in order to derive some economic considerations. This is one of the first exercises trying to empirically analyze this nexus, nevertheless the complex interactions and policy implications that consider all three sectors together, need more investigation and study in order to effectively support decision-making.

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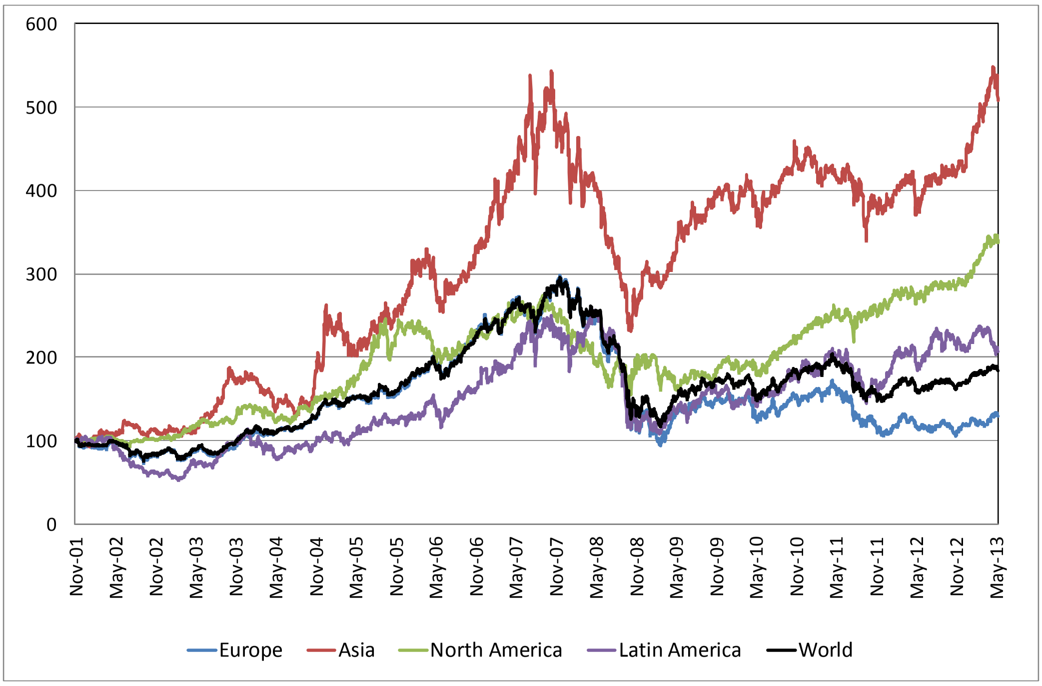
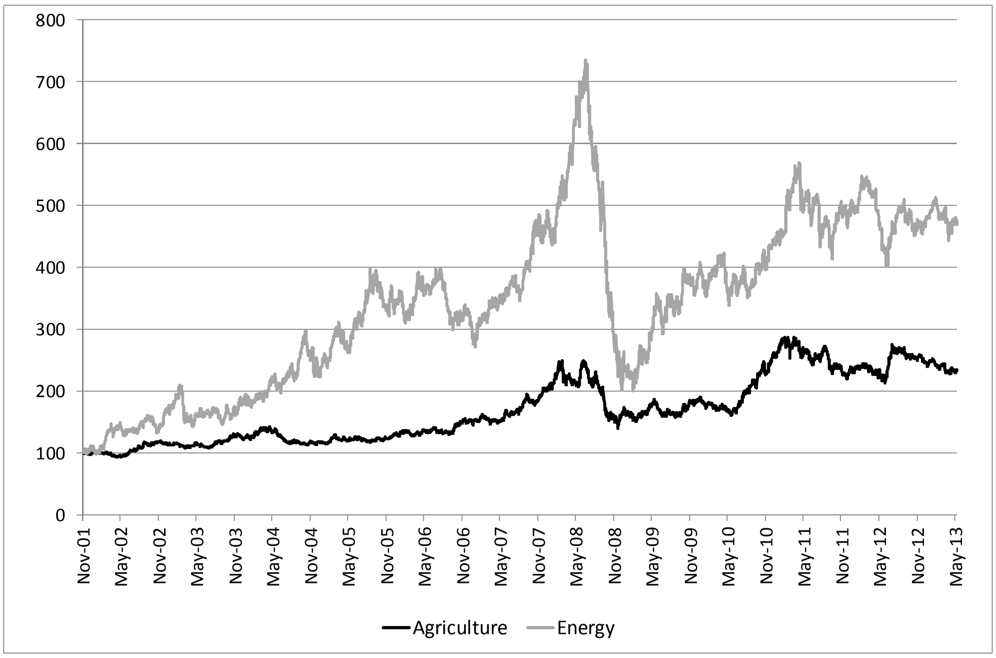
Tables and Figures

Figure 1 – Water indexes



Source: our elaboration on Datastream data

Figure 2 – Agricultural and Energy indexes



Source: our elaboration on Datastream data

Table 1 - Descriptive statistics of daily returns

	Europe Water index	*Asia Water index*	*North America Water index*	*Latin America Water index*	*World Water indexes*	*Agriculture price index*	*Energy price index*
Obs.	3007	3007	3007	3007	3007	3007	3007
Mean	0.008	0.054	0.041	0.024	0.034	0.028	0.052
Median	0.009	0	0.001	0.078	0.070	0	0.025
Std. Dev.	1.424	1.557	1.328	1.686	1.119	1.096	1.982
Kurtosis	7.32	5.16	7.43	4.99	8.17	2.66	2.13
Skewness	-0.030	0.498	0.361	-0.550	-0.306	-0.218	-0.123
Minimum	-10.09	-9.24	-7.56	-12.26	-8.07	-5.81	-9.35
Maximum	13.97	13.27	12.14	10.55	10.90	5.72	9.81
t-statistic	0.325	1.904	1.679	0.786	0.991	1.416	1.434

Source: our elaboration on Datastream data

*Note: Descriptive statistics are presented for continuously compounded daily returns calculated as 100*ln(pt/pt-1) where pt is daily index.*

Table 2 – Multivariate GARCH estimates and diagnostic test

	Europe		Asia		North America		Latin America		World DS	
	Coeff.	*P-value*	Coeff.	*P-value*	Coeff.	*P-value*	Coeff.	*P-value*	Coeff.	*P-value*
mean equation										
$m_{1,1}$	**0.054**	*0.002*	-0.019	*0.289*	**-0.059**	*0.001*	**0.036**	*0.067*	**0.071**	*0.000*
$m_{1,2}$	0.024	*0.225*	**0.083**	*0.000*	-0.021	*0.220*	**0.072**	*0.007*	**0.036**	*0.015*
$m_{1,3}$	0.013	*0.218*	**0.041**	*0.001*	0.013	*0.164*	0.011	*0.435*	**0.014**	*0.067*
$m_{1,0}$	**0.068**	*0.000*	**0.056**	*0.013*	**0.053**	*0.003*	**0.056**	*0.030*	**0.065**	*0.000*
$m_{2,1}$	-0.005	*0.721*	-0.006	*0.540*	0.009	*0.457*	0.005	*0.637*	-0.003	*0.857*
$m_{2,2}$	0.022	*0.239*	0.026	*0.118*	0.023	*0.160*	**0.029**	*0.086*	0.023	*0.173*
$m_{2,3}$	**-0.022**	*0.008*	**-0.026**	*0.001*	**-0.020**	*0.009*	**-0.023**	*0.002*	**-0.023**	*0.004*
$m_{2,0}$	0.025	*0.134*	**0.028**	*0.072*	0.021	*0.151*	0.024	*0.119*	0.024	*0.127*
$m_{3,1}$	0.001	*0.965*	**-0.034**	*0.063*	0.034	*0.143*	**0.034**	*0.065*	0.003	*0.912*
$m_{3,2}$	0.040	*0.185*	**0.054**	*0.052*	**0.047**	*0.075*	**0.053**	*0.056*	0.042	*0.109*
$m_{3,3}$	**-0.035**	*0.048*	**-0.037**	*0.021*	**-0.034**	*0.027*	**-0.042**	*0.007*	**-0.038**	*0.023*
$m_{3,0}$	**0.080**	*0.009*	**0.075**	*0.007*	**0.064**	*0.016*	**0.076**	*0.007*	**0.081**	*0.003*
$c_{1,1}$	**0.017**	*0.004*	**0.059**	*0.002*	**0.016**	*0.008*	**0.294**	*0.000*	**0.016**	*0.000*
$c_{2,2}$	**0.009**	*0.021*	**0.009**	*0.000*	**0.007**	*0.000*	**0.008**	*0.000*	**0.008**	*0.000*
$c_{3,3}$	**0.027**	*0.003*	**0.032**	*0.000*	**0.033**	*0.000*	**0.047**	*0.000*	**0.030**	*0.000*
variance equation										
$a_{1,1}$	**0.055**	*0.000*	**0.074**	*0.000*	**0.071**	*0.000*	**0.071**	*0.000*	**0.062**	*0.000*
$a_{1,2}$	-0.006	*0.599*	0.015	*0.337*	-0.012	*0.379*	0.001	*0.973*	**-0.014**	*0.030*
$a_{1,3}$	0.008	*0.279*	0.000	*0.960*	**0.009**	*0.083*	**0.043**	*0.016*	**0.009**	*0.000*
$a_{2,1}$	-0.012	*0.134*	0.003	*0.596*	**-0.021**	*0.000*	**-0.011**	*0.003*	**-0.019**	*0.001*
$a_{2,2}$	**0.039**	*0.000*	**0.042**	*0.000*	**0.038**	*0.000*	**0.035**	*0.000*	**0.038**	*0.000*
$a_{2,3}$	0.008	*0.265*	0.002	*0.705*	**0.007**	*0.028*	**0.008**	*0.096*	**0.009**	*0.013*
$a_{3,1}$	**0.020**	*0.087*	0.000	*0.981*	0.014	*0.189*	0.005	*0.526*	**0.018**	*0.089*
$a_{3,2}$	-0.022	*0.146*	-0.010	*0.218*	**-0.020**	*0.002*	**-0.021**	*0.041*	**-0.018**	*0.100*
$a_{3,3}$	**0.037**	*0.000*	**0.041**	*0.000*	**0.038**	*0.000*	**0.039**	*0.000*	**0.038**	*0.000*
$b_{1,1}$	**0.933**	*0.000*	**0.913**	*0.000*	**0.923**	*0.000*	**0.802**	*0.000*	**0.922**	*0.000*
$b_{1,2}$	0.017	*0.608*	**-0.281**	*0.012*	**0.056**	*0.038*	0.142	*0.422*	**0.021**	*0.000*
$b_{1,3}$	-0.002	*0.920*	0.031	*0.306*	**-0.039**	*0.004*	-0.051	*0.464*	**-0.008**	*0.031*
$b_{2,1}$	0.031	*0.151*	0.017	*0.350*	**0.043**	*0.000*	**0.046**	*0.006*	**0.042**	*0.000*
$b_{2,2}$	**0.955**	*0.000*	**0.951**	*0.000*	**0.955**	*0.000*	**0.957**	*0.000*	**0.955**	*0.000*
$b_{2,3}$	-0.018	*0.230*	-0.004	*0.428*	**-0.009**	*0.015*	**-0.024**	*0.009*	**-0.018**	*0.008*
$b_{3,1}$	**-0.049**	*0.027*	-0.023	*0.118*	**-0.073**	*0.000*	**-0.072**	*0.002*	**-0.048**	*0.008*
$b_{3,2}$	**0.054**	*0.098*	0.018	*0.164*	**0.058**	*0.000*	**0.102**	*0.001*	**0.046**	*0.041*
$b_{3,3}$	**0.954**	*0.000*	**0.951**	*0.000*	**0.950**	*0.000*	**0.944**	*0.000*	**0.952**	*0.000*
θ_1	**0.013**	*0.000*	**0.008**	*0.001*	**0.010**	*0.000*	**0.008**	*0.000*	**0.014**	*0.000*
θ_2	**0.984**	*0.000*	**0.991**	*0.000*	**0.988**	*0.000*	**0.990**	*0.000*	**0.984**	*0.000*
Log L	-14,859.9		-15,363.9		-14,784.9		-15,656.8		-14,129.1	
AIC	9.93		10.27		9.88		10.46		9.44	
SBC	10.00		10.34		9.95		10.53		9.51	
HQ	9.96		10.29		9.91		10.49		9.47	

Note: Model estimated using QMLE by BFGS algorithm. The order of variables is the following: Water (1), Agriculture (2) and Energy (3). In the mean equation c denotes the constant terms. In the variance equation a denotes the estimated Arch terms and b denotes the estimated GARCH terms. P-value in italic.

Table 3 – Diagnostic tests for standardized residuals

	Europe		Asia		North America		Latin America		World	
	Statistic	*p-value*	Statistic	*p-value*	Statistic	*p-value*	Statistic	*p-value*	Statistic	*p-value*
Q(12)	105.275	*0.556*	103.332	*0.609*	73.266	*0.996*	75.746	*0.992*	94.777	*0.814*
Q(20)	180.221	*0.481*	194.483	*0.218*	139.533	*0.989*	137.066	*0.993*	170.544	*0.682*

Note: Q(12) and Q(20) denote the Ljung-Box test statistic on returns. p-value in italics. The null hypothesis is that there is no autocorrelation up to order 12 and 20 for standardized residuals.

Table 4 - Mean value of DCC, before and after the financial crisis of September 2008

Period	*Europe*	*Asia*	*North A.*	*Latin A.*	*World DS*
before Sept., 18 2008	0.16	0.11	0.11	0.15	0.15
after Sept., 18 2008	0.38	0.27	0.31	0.38	0.42

Source: based on our calculations

Figure 3 – Time-varying conditional correlations

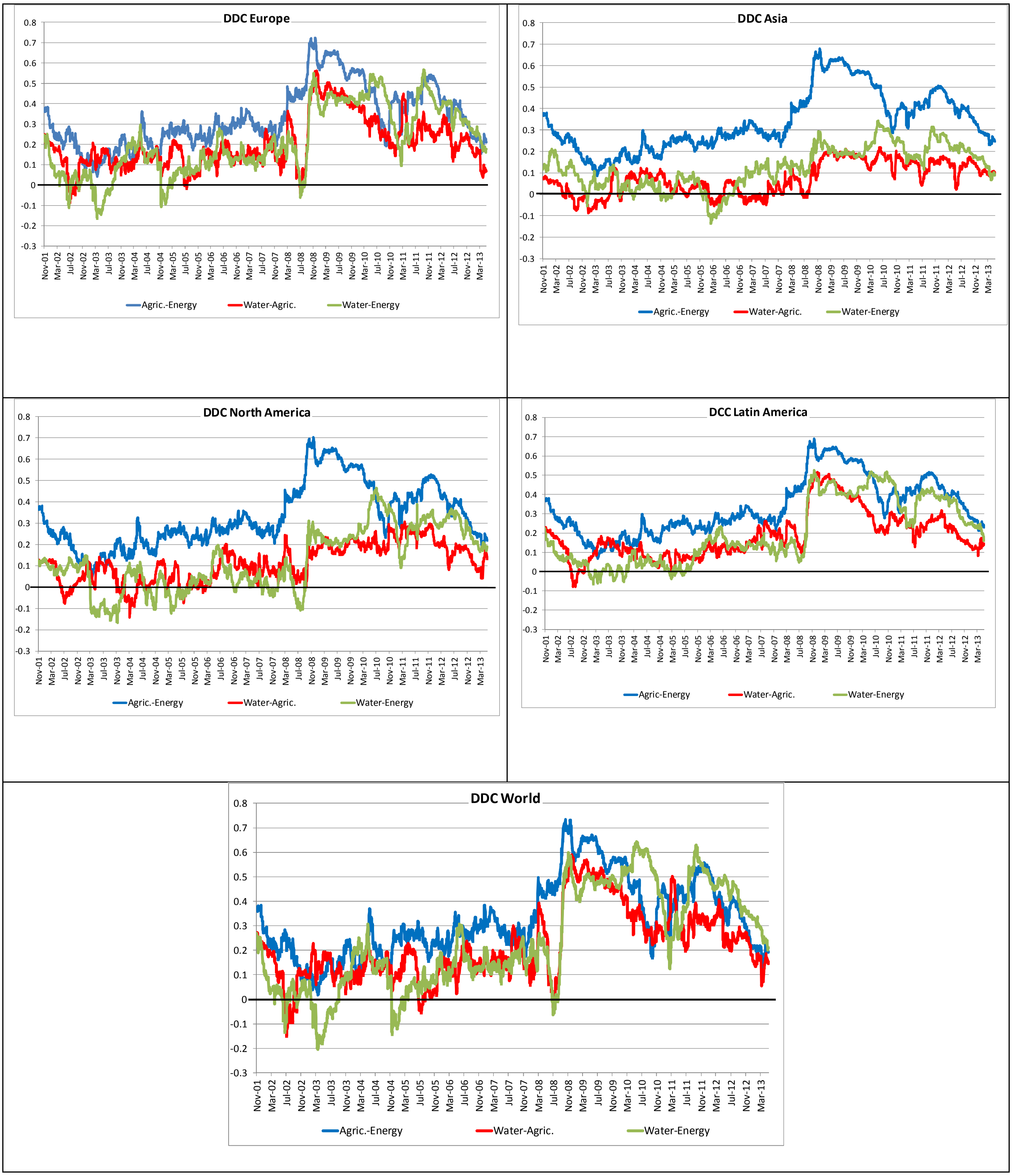


Figure 4 – Geographical area dynamic Nexus: mean value of DCC between agriculture-energy, water-agriculture and water-energy