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An Analysis of the Relationship between WTI Term Structure and Oil Market Fundamentals in 2002-2009 [δ]

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Abstract

The main objective of this paper is to analyze the behavior of the term structure of the WTI futures market between 2002 and 2009, period known by a sustained price rise followed by a price slump and again by a new price rise. To achieve this goal, we use Principal Component Analysis (PCA) to decompose WTI futures price series into components which are used to explain series variability (e.g. changes in its term structure). After it, we try to identify how changes in oil markets fundamentals (physical and financial) may have contributed to oil futures term structure variability. The impact of these variables on WTI term structure is assessed using impulse-response functions and variance decomposition analysis. This work is of interest to market analysts, hedgers, and traders, among others, because it helps to clarify how changes in oil markets may affect their strategies in these markets.

JEL Classification: C14; C32; G13; Q49

Keywords: WTI Term Structure; Principal Components Analysis; VARXs Models; Futures Pricing; Oil Market Fundamentals

1. Introduction

During the last few years, crude oil futures markets have attracted a lot of attention from specialised media and academics. However, while the first group has focused most of its attention on the possible influence of speculation in these markets on crude oil spot pricing, the second one has discussed a relatively broad array of topics, ranging from the mentioned subject (Merino & Ortiz (2005)), to segmentation in the crude oil futures (Lautier (2004a)) and the forecast of crude oil term structure (Chantziara & Skiadopoulos (2008)). In our view, considering the crude oil price rise between 2004 and 2008, this interest probably reflects the awareness that crude oil futures markets can be a useful tool to access market expectations about prices in the future. For example, for practitioners, the term structure of petroleum futures is of great importance in terms of risk management and price discovery.

Within this context, the present work aims to answer the following questions: i) is it possible to find and establish a statistical significant relationship between the crude oil term structure and oil market fundamentals?; ii) are the changes in crude oil futures prices consistent with changes in market fundamentals?; iii) is there any linkage between crude oil spot prices and futures prices?; and iv) does the way crude oil term structure and market fundamentals relate to each other change when more information becomes available?

In order to try answering these questions, our analysis will focus on the West Texas Intermediate (WTI) markets. This choice can be justified by the fact that this is the benchmark for most of the crude oil transactions that occur between the USA (the biggest national market in the world for this commodity, and also the most liquid) and crude oil exporters, and because of the large data availability on fundamental variables for this market (the USA).

This paper is structured as follows. After this introduction, section two discusses briefly the statistical and econometric methodology we use in this work (namely, principal component analysis, and VARX models). Section three describes the dataset and discusses the results for stationarity tests for the variables in this dataset. Section four presents the empirical analysis, including the way we develop our approach to try to answer the questions put above, the statistical results, and our interpretation for them. Section five concludes this study.

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2. Principal Component Analysis and VARX Analysis

2.1. Principal Component Analysis

The main objective of Principal Component Analysis (PCA) is to explain the systematic behavior of a given set of observable variables (e.g. x_1, x_2, ..., x_p) through a (smaller) set of latent variables. Technically speaking, this method works by means of a transformation from the original set of random variables to a new (orthogonal) set which has a covariance matrix whose structure is similar to the original set.

To see this, assume that there are two matrices, X $(=\lfloor x_{t1} \quad x_{t2} \quad \ldots \quad x_{tp} \rfloor$, with $t = 1,2,...,T$) as the original set of variables, and Z which represents the original variables after a proper transformation (e.g. PCs, or principal components). Then,

$$Z = XA \tag{1}$$

where $A_{(pxp)}$ is the matrix which represents the proper transformation (orthonormal matrix); Z has dimension (Txp).[1]

If you consider the i-th PC (z_i), where A_i is a column-vector of A ($i = j = 1,2,..., p$), we have

$$z_i = XA_i \tag{2}$$

or $z_1 = XA_{i=1}$, $z_2 = XA_{i=2}$, ... , $z_p = XA_{i=p}$ (each z_i with dimension $Tx1$). Notice that matrix A contains the eigenvectors of X´s covariance matrix (i.e. $S = E(X^T X)$), where the variance of i-th principal component is equal to the i-th eigenvalue of X (λ_i).

Using the terminology of linear algebra, PCA is simply a change of basis, where the X matrix is re-expressed in terms of a new (orthonormal) basis, which is a linear combination of the original basis. So, what would be an appropriate new basis (Z) for X ? The principle behind this choice is to select *p* normalized directions in a *p*-dimensional space along which the variance in X is "maximized" (i.e. the terms representing covariances are minimized such that they become zero), with each pair of directions orthonormal to each other.

These choices are then ranked in the following fashion: first, the direction with the highest variance; second, the direction with the second highest variance, and so, on until (in some cases) *p* directions are selected. These are the PCs of X .

In order to achieve this goal, we need two assumptions: i) Z must be an orthonormal matrix; ii) the directions with the largest variances are the most important (or most principal). With this in mind, the PCA objective can be summarized as follows: find an orthonormal matrix A which satisfies (1) such that Z´s covariance matrix is diagonalized. Following this idea, we can write this goal as a variance optimization (maximization) problem:

$$\max_{\|A_i\|=1} \quad A_i^T (X^T X) A_i \tag{3}$$

with a first order condition (A_i^* is the i-th vector which satisfies (3)) [2]

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[1] If we use some intuition, we may think of Z and A as (Txq) and (pxq) matrices, with $q \leq p$. This is so if we consider that most of (or all) variation in the original dataset may be accounted by q PCs.

[2] Note that A_i^* is a vector which maximizes (3), with A_i^* associated to λ_i^*, which is the highest eigenvalue of matrix *S* (for the first PC), the second highest eigenvalue of this matrix (for the second PC), and so on.

$$(X^T X - \lambda_i^* I)A_i^* = 0 \tag{4}$$

where $I_{(pxp)}$ is an identity matrix, λ_i ($i = 1,2,..., p$) is the i-th Lagrange multiplier (eigenvalue), A_i is a column-vector of A (equal to the i-th $X^T X$ eigenvector which corresponds to λ_i), and $0_{(px1)}$ is a null column-vector.

Another way to write the maximization problem (whose first order condition is given by (4)) is

$$\begin{gathered} A_i = \arg \max_{\|A_i\|=1} Var(XA_i) \\ \text{s.t. } \langle A_k , A_i \rangle = 0 \text{, } \forall k < i \end{gathered} \tag{5}$$

where the restriction $\langle A_k , A_i \rangle = 0$ indicates that A´s eigenvectors must be orthogonal in order to assure that (3) has nontrivial solutions.[3]

So, the Z´s covariance matrix is given by

$$Var(Z) = E(Z^T Z) = E(A^T X^T XA) = \begin{bmatrix} \lambda_1 & 0 & \dots & 0 \\ 0 & \lambda_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \lambda_p \end{bmatrix} \tag{6}$$

where $\lambda_1 = Var(XA_{i=1})$, $\lambda_2 = Var(XA_{i=2})$, ..., $\lambda_p = Var(XA_{i=p})$, and $Cov(z_i , z_h) = 0$, $\forall i \neq h$, i.e. PCs are orthogonal to each other.

2.2. VARX Analysis

We use VAR(X) methodology to achieve two goals: i) to determine the sets of endogenous/exogenous variables which will enter VARX models using block exogeneity tests; and ii) after step (i), to estimate VARX models for each one of the aforementioned sets in order to generate impulse-response functions and decompose the variance of the endogenous variables in each set. These points will be discussed in more detail in subsections 4.2 and 4.3.

The VARX methodology, which is used to generate impulse-response functions and decompose the variance for each set of variables in our analysis, can be described as follows: let Y and W be vectors of endogenous and exogenous variables, respectively. Then a VARX in reduced (or standard) form for each set of variables is

$$Y_t = B_0 + B_1 Y_{t-1} + B_2 Y_{t-2} + \ldots + B_k Y_{t-k} + C_1 W_{t-1} + C_2 W_{t-2} + \ldots + C_k W_{t-k} + \Psi_t \tag{7}$$

where Y has dimension $(mx1)$, B_j is (mxm), C is (mxn), W is $(nx1)$, and Ψ_t is a $(mx1)$ vector of error terms. Note that $1 \leq m \leq r + 1$ and $n \leq r$ such that $m + n = r + 1$, with $r = \#\ fundamentals$.

So, one way to obtain impulse response functions is rewriting equation (7) in its structural form and using Cholesky decomposition. Also, variance decomposition can be obtained through the use of Cholesky factorization.

[3] This condition implies that matrix *A* has no null eigenvalue, i.e. it is nonsingular. Otherwise there would be one or more perfect linear relationships among the column-vectors of *A*, resulting in a column dimension smaller than *p* (or $|A| = 0$). So, we would have $n < p$ *PCs*. See footnote 1.

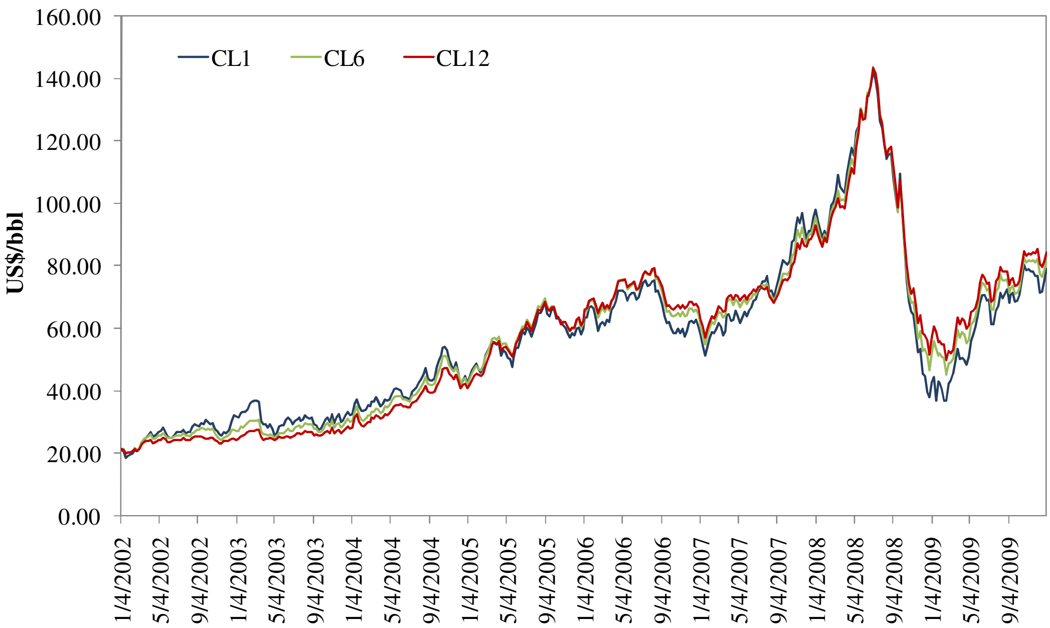
3. Description of the Data Set and Stationarity Tests

3.1. Data

In this work, we use weekly data for the following variables: nominal WTI futures quotes from 1st to 12th month in the New York Mercantile Exchange (NYMEX); US refining utilization rates; US crude oil and gasoline inventories; crude oil and diesel/gasoil inventories in Europe; OPEC spare capacity; commercial and noncommercial net positions in WTI futures and options markets; nominal interest rates for US T-Bills.[4] The data sources are: Bloomberg; US Department of Energy (EIA-DOE); International Energy Agency (IEA); US Commodities, Futures, and Trading Commission (CFTC); and US Federal Reserve. [5]

The sample spreads from January 2002 to December 2009, comprising 418 data points (weeks) for each variable. Figure 1 shows WTI weekly average quotes for the following maturities 1^{st}, 6^{th}, and 12^{th} month (CL1, CL6, CL12) for the time interval mentioned above. The time path for other maturities is very much like those depicted in Figure 1.

Chart 1 – WTI Future Contract Prices (1st, 6th, 12th month) – Weekly Averages: January/2002-December/2009



Source: Bloomberg

At a glance, it is easy to see that time paths for CL1, CL6, and CL12 are very similar for the time period considered, with small differences among them probably due to their volatilities (standard deviations) - as maturity increases, liquidity decreases, and volatility increases (see Table 1). Another way to look at Figure 1 is to fix *t* (choosing a specific week), and draw a vertical line from fixed *t* (bottom) to top, and then read the quotes for each contract – you´ve got a caricature for WTI term structure in any given week.

Table 1 shows the main descriptive statistics for WTI futures contracts.

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[4] The weekly quotes for the first 12 months of WTI futures contracts are means of daily closing prices for these contracts in each corresponding week. In order to obtain weekly data from monthly data (OPEC spare capacity, crude oil and diesel/gasoil stocks in Europe), we used moving averages centered at each week for all months from January 2002 to December 2009. Each month was transformed in its equivalent number of weeks. So, the desired data point for each week is the weighted average between the previous and the following month, where the weight of a given month is directly proportional to its proximity to a specific week.

[5] We assume that each market agent works with his/her own inflation expectation (which is expected to be invariant to each agent´s choices), regardless of whether he or she is comparing either different portfolio alternatives or computing the effective cost of hedging a given amount of barrels of crude oil. So, in this paper all price and interest rate variables are nominal rather than real, which means that inflation market expectations are only implicitly considered in our modeling.

Table 1 – Descriptive Statistics for WTI Futures Contracts

	CL1	CL2	CL3	CL4	CL5	CL6	CL7	CL8	CL9	CL10	CL11	CL12
WTI (weekly prices, level)												
Mean	57.031	57.403	57.609	57.703	57.744	57.756	57.743	57.716	57.681	57.641	57.598	57.554
Standard Deviation	25.738	25.825	25.974	26.136	26.299	26.452	26.591	26.712	26.817	26.908	26.990	27.065
Kurtosis	0.795	0.719	0.636	0.560	0.491	0.427	0.370	0.317	0.266	0.219	0.175	0.133
Skewness	0.946	0.886	0.834	0.791	0.754	0.722	0.694	0.669	0.646	0.625	0.605	0.588

Note: CLp ($p = 1,2,...,12$) denotes the WTI futures contract which expires at the beginning of j-th month. Source: Author´s estimates from Bloomberg data

Finally, it is important to mention what our eyes cannot ignore: Figure 1 suggests that WTI futures prices may not be stationary, which takes us to the next subsection of this work.

3.2. Stationarity and Unit Root Tests

In this subsection we test for stationarity and the presence of unit roots for all data used in this work. The idea of performing both tests is to try to avoid an inappropriate choice when deciding to differentiate or not a series due to possible inconsistencies between the results of these tests. So, if a given variable, after taking its nth difference ($n = 0,1,2$), is considered stationary according to stationarity (KPSS) and unit root (ADF) tests, we can conclude there is no ambiguity regarding the number of differences one must take to make this variable stationary.[6] The problem occurs when these tests give contradictory results. This point will be discussed in what follows when considering the test results for our dataset.

It is important to say that, despite the usual methodology suggestion to standardize all series from a dataset before estimating PCs, in this paper we adopt Chantziara & Skiadopoulos (2008) approach, who worked with daily changes (first differences) of WTI, Brent, motor gasoline and heating oil future contracts.[7]

Also, to obtain valid PC estimates, the futures contracts series must be (weakly) stationary, which means that they have to have constant mean and finite variance (i.e. the *S* covariance matrix must be constant for any *t*).[8] If this condition is not met when $t \to \infty$, the maximization problem in (2) will not have a solution.[9]

Saying this, we now turn our attention to the results of the tests for stationarity (KPSS) and unit root (Augmented Dickey-Fueller (ADF)), which are shown in tables 2 and 3. The fundamental variables are defined in the following way: OPEC spare capacity (*OPEC_Spare*)[10], crude oil commercial stocks in Europe (*Crude_Stocks_Eur*) and in the US (*USA_Crude_Stocks*), US gasoline stocks (*USA_Gas_Stocks*), gasoil and diesel stocks in Europe (*Dest_Stocks_Eur*), US refinery capacity utilization 4-weeks average (*USA_Ref_FUT*), commercial (*WTI_Comm_net*) and noncommercial (*WTI_Noncomm_net*) net positions in crude oil (WTI) futures and options markets (NYMEX), interest rates (T-Bills) from the Federal Reserve (USA) for varying maturities (*US_Treas_1m_pm*, *US_Treas_3m_pm*, *US_Treas_3m_pq*, *US_Treas_6m_ps*, *US_Treas_1y_py*), and interest rates spreads between different maturities (*US_Treas_Spread_6m_1m*, *US_Treas_Spread_1y_3m*).[11] This set also includes a proxy for WTI spot price (i.e. *WTI_front_mth* or CL1).[12]

[6] We do not make cointegration tests here because as it will become evident in the present subsection and in subsection 4.1, all sets of variables included in each VAR in the endogeneity/exogeneity tests and in the estimated VARXs are composed by series with different orders of integration (i.e. $I(0)$, $I(1)$, and $I(2)$). In this situation, as Enders (2004) points out, according to Engle and Granger´s original definition of cointegration, "if two variables are integrated of different orders they cannot be cointegrated" (p. 322-323). Consequently, it is preferable to estimate the VAR(X)s models only after taking the number of differences necessary to make the relevant series stationary.

[7] Manly (2008) and Tsay (2005) are examples of the traditional methodology.

[8] An additional condition for weak stationarity in this case is that the X´s cross covariance matrix must be dependent only of the *lag/lead* between two variables in t_1 and t_2, for $\forall t_1, t_2$, $t_1 \neq t_2$ (i.e. their covariance is time-invariant).

[9] To see this, recall that (5) is equivalent to (3).

[10] OPEC Spare Capacity refers to OPEC 12 + Iraq (i.e. Algeria, Angola, Ecuador, Indonesia, Iran, Kuwait, Libya, Nigeria, Qatar, Saudi Arabia, United Arab Emirates, Venezuela, and Iraq).

[11] Note that 1m denotes T-Bill at 1-month maturity, 3m T-Bill at 3-month maturity, 6m T-Bill at 6-month maturity, and 1y T-Bill at 1-year maturity. Also, pm refers to monthly rates, pq to quarterly rates, ps to semestral rates, and py to yearly rates. For interest rate spreads, 6m_1m is the spread between 6-month and 1-month T-Bills; 1y_3m is the spread between 1-year and 3-month T-Bills. These

Table 2 – Stationarity/Unit Root Tests Results (WTI Futures Contracts)

Variable (Contract)	Stationary in	Test (*)	p-value (KPSS; ADF) (**)	Specification
CL1	1st difference	ADF, KPSS	> 0.05; 0.0002	Constant, no time trend
CL2	1st difference	ADF, KPSS	> 0.05; 0.0002	Constant, no time trend
CL3	1st difference	ADF, KPSS	> 0.05; 0.0002	Constant, no time trend
CL4	1st difference	ADF, KPSS	> 0.05; 0.0002	Constant, no time trend
CL5	1st difference	ADF, KPSS	> 0.05; 0.0001	Constant, no time trend
CL6	1st difference	ADF, KPSS	> 0.05; 0.0001	Constant, no time trend
CL7	1st difference	ADF, KPSS	> 0.05; 0.0001	Constant, no time trend
CL8	1st difference	ADF, KPSS	> 0.05; 0.0001	Constant, no time trend
CL9	1st difference	ADF, KPSS	> 0.05; 0.0001	Constant, no time trend
CL10	1st difference	ADF, KPSS	> 0.05; 0.0001	Constant, no time trend
CL11	1st difference	ADF, KPSS	> 0.05; 0.0001	Constant, no time trend
CL12	1st difference	ADF, KPSS	> 0.05; 0.0001	Constant, no time trend

Notes: CLp ($p = 1,2,...,12$) denotes the WTI futures contract which expires at the beginning of j-th month; total number of observations: 418 (level); (*) ADF is the Augmented Dickey-Fueller Test for unit root (H0: y_t is $I(1)$), KPSS is the Kwiatkowski-Phillips-Schmidt-Shin test for stationarity (H0: y_t is stationary), and JCH is the Joint Confirmation Hypothesis for ADF and KPSS tests (see Carrion-i-Silvestre et al. (2001) and Kębłowski & Welfe (2004)); (**) p-value is the significance level in the ADF (KPSS) test necessary to (not) reject H0; for JCH, p-value refers to critical values for the rejection of the null hypothesis (joint confirmation hypothesis) of unit root (see Kębłowski & Welfe (2004)). Source: Author´s estimates

Table 3 – Stationarity/Unit Root Tests Results (Fundamentals)

Variable	Stationary in	Test (*)	p-value (KPSS; ADF) (**)	Specification
WTI_front_mth (CL1)	1st difference	ADF, KPSS	> 0.05; 0.0002	Constant, no time trend
OPEC_Spare	1st difference	ADF, KPSS	> 0.05; 0.0000	Constant, no time trend
Dest_Stocks_Eur	1st difference	ADF, KPSS	> 0.05; 0.0000	Constant, no time trend
Crude_Stocks_Eur	Level	JCH	0.05	Constant, no time trend
USA_Crude_Stocks	1st difference	ADF, KPSS	> 0.05; 0.0000	Constant, no time trend
USA_Gas_Stocks	Level	ADF, KPSS	> 0.05; 0.0000	Constant, no time trend
USA_Ref_FUT	1st difference	ADF, KPSS	> 0.05; 0.0000	Constant, no time trend
WTI_Comm_net	1st difference	JCH	0.01	Constant, no time trend
WTI_Noncomm_net	1st difference	JCH	0.01	Constant, no time trend
US_Treas_1m_pm	2nd difference	JCH	0.01	Constant, no time trend
US_Treas_3m_pq	2nd difference	JCH	0.01	Constant, no time trend
US_Treas_6m_ps	2nd difference	JCH	0.01	Constant, no time trend
US_Treas_1y_py	2nd difference	JCH	0.01	Constant, no time trend
US_Treas_3m_pm	2nd difference	JCH	0.01	Constant, no time trend
US_Treas_Spread_6m_1m	1st difference	ADF, KPSS	> 0.05; 0.0000	Constant, no time trend
US_Treas_Spread_1y_3m	1st difference	JCH	0.01	Constant, no time trend

Notes: Total number of observations: 418 (level); (*) ADF is the Augmented Dickey-Fueller Test for unit root (H0: y_t is $I(1)$), KPSS is the Kwiatkowski-Phillips-Schmidt-Shin test for stationarity (H0: y_t is stationary), and JCH is the Joint Confirmation Hypothesis for ADF and KPSS tests (see Carrion-i-Silvestre et al. (2001) and Kębłowski & Welfe (2004)); (**) p-value is the significance level in the ADF (KPSS) test necessary to (not) reject H0; for JCH, p-value refers to critical values for the rejection of the null hypothesis (joint confirmation hypothesis) of unit root (see Kębłowski & Welfe (2004)). Source: Author´s estimates

spreads were calculated using the following formula: $Spread_{tj} = ((1 + i_t)/(1 + i_j)) - 1$, where i_t is the interest rate of a bond with maturity at t, and i_j is the interest rate of a bond with maturity at j, with $t > j$.

[12] The reason for inclusion of a WTI spot price proxy in the set of fundamentals will become clear later.

When performing ADF tests for the presence of unit roots in one or more series from our dataset, we follow Patterson (2000) procedure, who suggests that one must first find the number of unit roots beginning with the alternative hypothesis H1: $y_t \sim I(2)$, and then take the appropriate number of differences to make them stationary, if necessary. [13] Also, since the ADF test has low power for cases when the coefficient $\gamma = (\phi - 1)$ of y_{t-1} in the test equation is such that $0 < |\phi - 1| < 1$ but $|\phi - 1| \approx 0$, this procedure has the advantage of reducing the probability of occurrence of type II error.

With this in mind, we can see in table 2 that the hypothesis of nonstationarity (alternative hypothesis in KPSS test; null hypothesis in the ADF test) is rejected for all contract-months of WTI futures under consideration only when these series are taken in first differences. Table 3, on the other hand, shows a different picture, with few variables being stationary in levels, some variables being stationary only in first differences, while others only when taken in second differences. Also it is possible to see that some of the results shown in table 3 rely on KPSS and ADF tests, while others depend on what is known as ADF-KPSS test of joint confirmation hypothesis of unit root (henceforth JCH test, or simply JCH). [14] This is so because the results of KPSS and ADF tests were conflicting for some fundamental variables (*Crude_Stocks_Eur*, *WTI_Comm_net*, *WTI_Noncomm_net*, *US_Treas_1m_pm*, *US_Treas_3m_pq*, *US_Treas_6m_ps*, *US_Treas_1y_py*, *US_Treas_3m_pm*, and *US_Treas_Spread_1y_3m*), leading to ambiguity when deciding the appropriate number of differences to be taken to make them stationary.

The approach suggested in the literature to overcome this kind of problem [Charemza & Syczewska (1998), Carrion-i-Silvestre et al. (2001), and Kębłowski & Welfe (2004)], is to test a joint hypothesis for the presence of unit root (H0) when the ADF and KPSS tests are applied simultaneously (JCH). So, to check if the JCH is rejected for a given variable, we worked with asymptotical approximations for the critical values of ADF and KPSS tests statistics estimated by Kębłowski & Welfe (2004) using Monte Carlo simulations. [15]

As one can conclude from table 3, this method allows the rejection of the nonstationarity hypothesis (i.e. JCH) for all variables whose ADF and KPSS tests results were conflicting, once these series are taken in level, in first or second differences, when appropriate.

Finally, in terms of the previous studies, some of the results of this subsection are in line with Chantziara & Skiadopoulos (2008), who performed ADF tests for WTI futures contracts (CL1, CL2, …, CL9) for daily data from January 1993 to December 2003. Their results showed these series were stationary only when taken in first differences.

4. Empirical Analysis

4.1. Principal Components Estimation

As pointed out in subsection 3.2, to obtain valid estimates for principal components from a dataset, the variables included in this set must be stationary, which in our case justify the use of first differences of WTI futures quotes (recall the results in Table 2). So, after taking the first difference for WTI first 12-contract months series, we estimated the principal components for this data, using weekly observations from January 2002 to December 2009 (418 data points (weeks) for each series). [16] [17]

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[13] In other words, Patterson (2000) suggests inverting the usual ADF test approach, which works first checking if y_t is $I(1)$. In the case under consideration in the text, the null hypothesis is $H0: y_t \sim I(3)$, which does not make sense for economic time series, once most of them become stationary when taken in second differences (i.e. the rate of change of the rate of change). So, it is expected to reject *H0* in the first round of ADF tests.

[14] The joint confirmation hypothesis of unit root (JCH) is defined taking a joint probability density function of the KPSS and ADF tests statistics conditional on the direct equivalence between their test hypotheses. For more details, see Charemza & Syczewska (1998) and Carrion-i-Silvestre et al. (2001).

[15] Kębłowski & Welfe (2004) estimated approximations for the asymptotical critical values for the JCH test for the following joint probabilities: 0.85, 0.90, 0.95, 0.975, and 0.99.

[16] QQ-plot analysis of the first differences of 1st-12th contract-month quotes suggest that these series have univariate t-Student distributions with 3 degrees of freedom. Notwithstanding, it does not necessarily mean that these variables have a t-Student multivariate distribution. See Meucci (2005), p. 79.

[17] Some authors point out that if the X variables are not normally distributed, PCA may not properly identify the original independent variables (e.g. the first PC may not necessarily reflect the direction with the first highest variance, etc.). However, in this work, we rely on Jolliffe (2002) and Dudziński et al. (1975), who say normality is not a necessary assumption for the multivariate

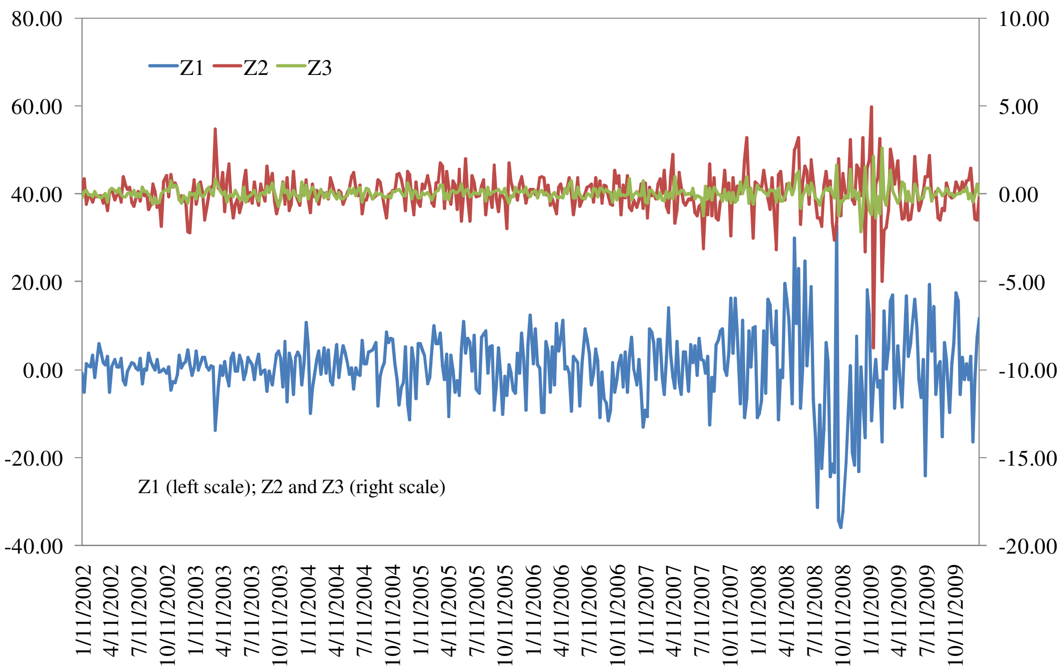
Table 4 presents the results of principal component analysis (PCA) in terms of variance and cumulative variance explained by each PC, including also regressions R-squared (see table 4´s note for details). Figure 2 shows the principal components (PCs) obtained as part of PC analysis. Results in Table 4 indicate that the first three PCs (considering a maximum theoretical possibility of 12 PCs ($p = 12$)) explain 100% of the variance of the weekly changes in WTI futures quotes. It also shows that the first PC (z_1) explains approximately 98% of this variance, while the second and third PCs (z_2 and z_3, respectively) appear to have a marginal role in explaining WTI weekly changes variance. Descriptive statistics for the first three WTI PCs (z_1, z_2, and z_3) are shown in Table 5.

Table 4 –WTI Term Structure Variance Explained by PCs and PCs Fit (%)

	WTI Total Explained Variance		PCs Fit to Data	
PCs	**Cumulative Variance Explained**	**Variance Explained by Each PC**	**Regressions R-Squared (*)**	
z_1	97.9	97.9	**Minimum**	99.86
z_2	99.7	1.8	**Median**	99.98
z_3	100.0	0.3	**Maximum**	99.99

Note: (*) Regressions R-squared refer to the coefficients of determination (R2) for linear regressions between each WTI contract-month and a given PC. The correlation loadings for each PC are the estimated slope coefficients of these regressions. Source: Author´s estimates

Figure 2 – WTI Principal Components: January/2002-December/2009



Source: Author´s estimates

distribution of variables in the X matrix. In particular, according to Jolliffe (2002), PCA can be viewed as a descriptive technique, which means that many of its properties and applications have no need for explicit distributional assumptions. However, in some cases, it is also possible to hypothesize that X has a multivariate elliptical distribution (of which the multivariate normal and the multivariate t-Student are special cases). For more details, see Jolliffe (2002), p 394-395.

Table 5 – WTI PCs Descriptive Statistics

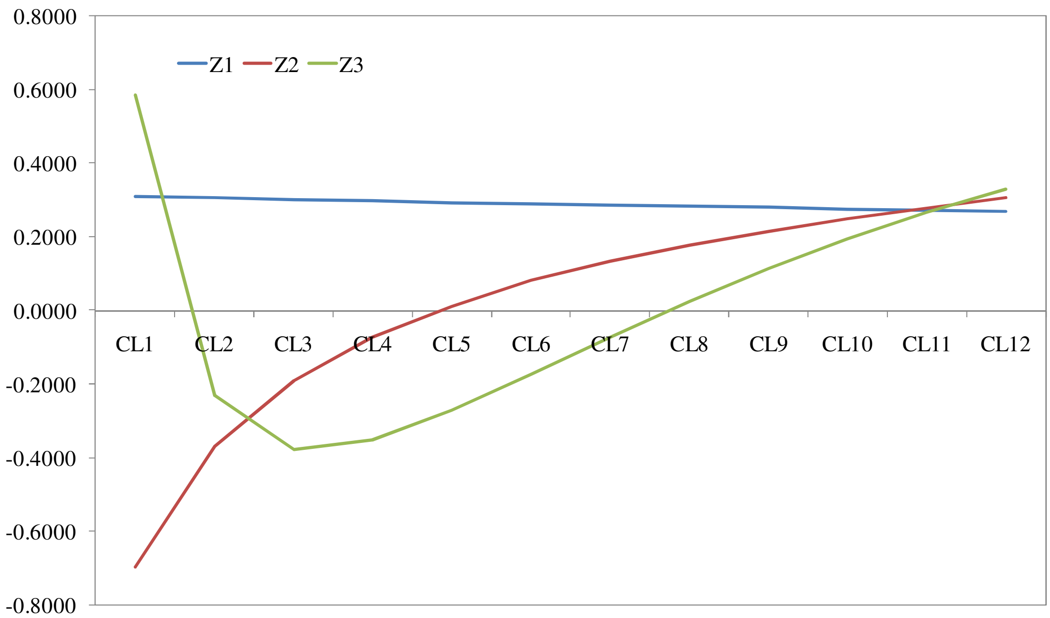
	PCs Statistics			
	Mean	**Standard Deviation**	**Kurtosis**	**Skewness**
z_1	0.503	8.378	3.341	-0.593
z_2	0.032	1.148	9.608	-0.935
z_3	0.012	0.414	7.789	0.715

Source: Author´s estimates

When interpreting WTI principal components we follow Litterman & Scheinkman (1991), who suggest that the first three PCs (i.e. z_1, z_2, and z_3), should be seen as indicators of <u>level</u>, <u>steepness</u>, and <u>curvature</u> of the term structure, respectively. In this fashion, the 1st PC explains vertical changes in the futures curve, while the 2nd and 3rd PCs explain changes in market regimes (i.e. from contango to backwardation and vice-versa). Following this argument, the 3rd PC can also be seen as a factor which is linked to changes in futures market volatility.[18]

Figure 3 shows the correlation loadings obtained for each PC (z_1, z_2, and z_3), which are the components of each eigenvector A_i ($i = 1,2,3$) of matrix A in (1). The a_{pi} element of eigenvector A_i ($p = 1,2,...,12$) is the weight that the price of pth contract month in WTI futures market has in the ith PC.

Figure 3 – Correlation Loadings for WTI



Source: Author´s estimates

So, according to the proposed interpretation for the WTI correlation loadings, z_1 can be seen as a factor which causes parallel shifts and in the same direction in the WTI term structure (1st – 12th months). The second PC (z_2) causes changes in one direction for contracts with shorter maturity (i.e. 1st – 4th months), and at the same time, changes in the opposite direction for contracts with longer maturities (5th – 12th months). This is clearly the factor responsible for market regime changes (from contango to backwardation, and vice-

[18] For more details, see Litterman & Scheinkam (1991) and Litterman et al. (1991).

versa). Finally, the curvature factor (z_3) is responsible for shifts in the futures curve in one direction for the first contract-month and contracts after the 7th month, while it does exactly the opposite for 2nd – 7th months. This is so because it probably reflects the relationship between this factor and the greater impact of volatility on first month than on last months (10th, 11th, 12th months) of the term structure.[19]

Also, it is important to say that, generally speaking, the results of this subsection are consistent with previous works which applied PCA to the term structure of crude oil futures markets [Tolmasky & Hindanov (2002), Lautier (2004b), Chantziara & Skiadopoulos (2008)].

4.2. Block Exogeinety Tests

In this subsection we determine the sets of endogenous and exogenous variables that will enter VARX estimation, impulse-response and variance decomposition analysis. As pointed out in the beginning of this work, to understand how changes in oil market fundamentals have affected WTI term structure in 2002-2009 (here represented by z_1, z_2, and z_3), we will use impulse-response and variance decomposition analysis to assess the different ways it happens. This analysis will be carried out in the next subsection.

Endogenous/Exogenous Variables

Working with all possible combinations of endogenous variables, after differencing some of them to achieve stationarity (see subsection 3.2), we estimated a total of 168 VARs (= 7 x 6 x4) and performed block exogeneity tests for each VAR.[20] In this first instance, all variables were treated as endogenous. Considering a p-value of 0.05, the results of these tests were used as a criterion for inclusion/exclusion of variables in the l-th VAR ($l = i \ x \ s \ x \ k$, where $i = 1,2,3$; $s = 1,2$; and $k = 1,2,3,4$).[21]

The variables excluded in the block exogeneity tests were included in these VARs as exogenous ones and as so used to form VARX models, which in the last step are the models estimated and which generate impulse-response functions and variance decompositions.

But, since in some cases our block exogeneity tests showed that more than one variable (endogenous or exogenous) with the same kind of information can be included in a VARX, we have to use some criterion to be parsimonious and avoid redundancy among the variables included in these models.[22] So, for each set (combination) of variables, we proceeded in the following way:

i) for cases when there were only exogenous variables which were redundant, we took the lowest (joint) p-values for each Granger equation in the block exogeneity tests (where these variables were dependent, or caused by the other variables) choosing those equations (variables) which have at least one explanatory variable with a p-value smaller or equal to 0.05. Then, we estimated a VARX for each one of those 'dependent' variables, which also included the endogenous variables previously determined, and the (non-

[19] Litterman et al. (1991) suggest that this pattern is the consequence of the transitory nature of volatility changes, since it follows a mean reverting process. The shape of correlation loadings curve for z_3 supports this view, given that a change in WTI 1st month quote (assuming $\Delta z_3 \neq 0$) will be bigger than changes in the back of the futures curve.

[20] In this step, the number of ways we can combine the endogenous variables is given by $(\#\,sets\ of\ core\ variables)x(\#\,net\ lentgh\ variables)x(\#\,interest\ rate\ variables)$ for each PC, considering only one lag choice (1 or 2 or 3 or 4). If the fact we are working with 3 PCs and four choices for the number of lags is considered, then the previous result becomes

$$(\#\,sets\ of\ core\ variables)x(\#\,net\ lentgh\ variables)x(\#\,interest\ rate\ variables)x3x4.$$

We define the core variables as those which cannot be arbitrarily excluded from any VAR (i.e. Δ*WTI_front_mth*, Δ*OPEC_Spare*, *Crude_Stocks_Eur*, Δ*Dest_Stocks_Eur*, Δ*USA_Crude_Stocks*, *USA_Gas_Stocks*, Δ*USA_Ref_FUT*); then $\#\,sets\ of\ core\ variables = 1$. Net length refers to noncommercial and noncommercial net positions, and interest rates to themselves (including spreads). With this in mind, we get the number 168.

[21] Notice that i index refers to the PCs, s index to the noncommercial and commercial variables, and k index to the number of lags used to estimate each VAR. So, the number of VAR(X)s models which will be estimated is 24 $(= 3x2x4)$.

[22] In this work, we say that two variables, $(X_i, X_j),\ i \neq j$, are redundant if the coefficient of correlation between them (ρ_{ij}) is equal or greater than 0.6. In terms of information sets, let Ω_{Xi} be the information set included in X_i, and $\overline{\Omega_{Xi}}$ be its complement which may be part of, say, X_j, with $\Omega_{Xi} \cap \overline{\Omega_{Xi}} = \emptyset$. Then, $\rho_{ij} \neq 0 \Leftrightarrow \Omega_{Xi} \cap \Omega_{Xj} \neq \emptyset$. Namely, we have here three sets of these variables: *WTI_Noncomm_net* and *WTI_Comm_net*; interest rates; and interest rates spreads.

redundant) exogenous variables; compared their Schwarz Information Criterion (SIC), and picked the model with the smallest SIC. This procedure results in the following sets (by PC and by number of lags)

Table 6 – Endogenous/Exogenous Variables Choices for VARXs (I)

	Endogenous Variables	Exogenous Variables
1 lag	z_1, ΔWTI_front_mth , ΔDest_Stocks_Eur , Crude_Stocks_Eur, ΔUSA_Crude_Stocks, ΔUSA_Ref_FUT, ΔWTI_Noncomm_net	ΔOPEC_Spare, USA_Gas_Stocks, Δ2_US_Treas_3m_pm
	z_1, ΔWTI_front_mth , ΔDest_Stocks_Eur , Crude_Stocks_Eur, ΔUSA_Crude_Stocks, ΔUSA_Ref_FUT, ΔWTI_Comm_net	ΔOPEC_Spare, USA_Gas_Stocks, Δ2_US_Treas_3m_pm
	z_2, ΔWTI_front_mth , ΔDest_Stocks_Eur , Crude_Stocks_Eur, ΔUSA_Crude_Stocks, ΔUSA_Ref_FUT, ΔWTI_Noncomm_net	ΔOPEC_Spare, USA_Gas_Stocks, Δ2_US_Treas_3m_pm
	z_2, ΔWTI_front_mth , ΔDest_Stocks_Eur , Crude_Stocks_Eur, ΔUSA_Crude_Stocks, ΔUSA_Ref_FUT, ΔWTI_Comm_net	ΔOPEC_Spare, USA_Gas_Stocks, Δ2_US_Treas_3m_pm
	z_3, ΔWTI_front_mth , ΔDest_Stocks_Eur , Crude_Stocks_Eur, ΔUSA_Crude_Stocks, ΔUSA_Ref_FUT, ΔWTI_Noncomm_net	ΔOPEC_Spare, USA_Gas_Stocks, Δ2_US_Treas_3m_pm
	z_3, ΔWTI_front_mth , ΔDest_Stocks_Eur , Crude_Stocks_Eur, ΔUSA_Crude_Stocks, ΔUSA_Ref_FUT, ΔWTI_Comm_net	ΔOPEC_Spare, USA_Gas_Stocks, Δ2_US_Treas_3m_pm
2 lags	z_1, ΔWTI_front_mth , ΔDest_Stocks_Eur , Crude_Stocks_Eur, ΔUSA_Crude_Stocks, ΔUSA_Ref_FUT, ΔWTI_Noncomm_net	ΔOPEC_Spare, USA_Gas_Stocks, Δ2_US_Treas_1y_py
	z_1, ΔWTI_front_mth , ΔDest_Stocks_Eur , Crude_Stocks_Eur, ΔUSA_Crude_Stocks, ΔUSA_Ref_FUT, ΔWTI_Comm_net	ΔOPEC_Spare, USA_Gas_Stocks, Δ2_US_Treas_1y_py

Note: ΔX denotes 1st difference of X; Δ2_X is the 2nd difference of X. Source: Author´s estimates

ii) for cases when there were endogenous and exogenous variables sharing the same set of information (i.e. being redundant), the procedure is straightforward: estimate VARXs combining the non-redundant variables (endogenous and exogenous), and the redundant ones (endogenous and exogenous) such that in each model we would have only one of each of these variables (one endogenous and one exogenous); choose the model with the smallest SIC. The results are shown in table 7.

At this point, it is important to say something about our lag choices.

<u>Number of Lags</u>

In order to determine the appropriate number of lags for each VAR (and block exogeneity tests) in the first step of our choice of variables procedure, we employed Schwarz Information Criterion (SIC). For most cases SIC suggested 1 lag with the exception of VARs which included 6-month interest rates as an endogenous variable. In these cases SIC indicated 2 lags as the best choice.

But, as a way to capture the dynamics of WTI future markets, we added 1, 2, and 3 lags to those VARs for which the block exogeneity tests were performed. The consequences of this choice were really interesting, since it allowed different combinations of endogenous and exogenous variables according to the number of lags per VAR.[23] So, in the following steps, we go on estimating all VARXs for 1, 2, 3, and 4 lags, as shown in the tables above.

As a final word, is important to say that all VARs and VARXs estimated as part of what of this subsection satisfied the stability condition. Now, we will turn to the estimation of the VARXs models.

[23] Our decision to add more lags to the number suggested by Schwarz Criterion can be justified in two ways: i) SIC is well known for picking the more parsimonious model (but also consistent for large samples), which in our case may throw away important information about the dynamics of future markets; ii) with very few exceptions, crude oil is not a commodity for instant delivery, and as such, there are a lot of transactions which take place along the weeks before the pricing of a future contract on a specific day. On the other hand, since the use of Akaike Information Criterion (AIC), which tends to suggest overparameterized models, pointed to a choice of 5 or 6 lags in most cases, we chose 4 (or 5) as the maximum number of lags to perform block exogeneity tests and to estimate the VARXs models (4 lags). We also think that this is the time window when a very significant part of the most important transactions (in terms of volume) in the crude oil markets occur.

Table 7 – Endogenous/Exogenous Variables Choices for VARXs (II)

	Endogenous Variables	Exogenous Variables
2 lags	z_2, ΔWTI_front_mth , ΔOPEC_Spare, ΔUSA_Crude_Stocks, USA_Gas_Stocks, ΔUSA_Ref_FUT, ΔWTI_Noncomm_net , Δ2_US_Treas_6m_ps	ΔDest_Stocks_Eur, Crude_Stocks_Eur, ΔUS_Treas_Spread_1y_3m
	z_2, ΔWTI_front_mth , ΔOPEC_Spare, ΔUSA_Crude_Stocks, USA_Gas_Stocks, ΔUSA_Ref_FUT, ΔWTI_Comm_net, Δ2_US_Treas_6m_ps	ΔDest_Stocks_Eur, Crude_Stocks_Eur, ΔUS_Treas_Spread_1y_3m
	z_3, ΔWTI_front_mth , ΔOPEC_Spare, ΔUSA_Crude_Stocks, USA_Gas_Stocks, ΔUSA_Ref_FUT, ΔWTI_Noncomm_net, Δ2_US_Treas_6m_ps	ΔDest_Stocks_Eur, Crude_Stocks_Eur, ΔUS_Treas_Spread_1y_3m
	z_3, ΔWTI_front_mth , ΔOPEC_Spare, ΔUSA_Crude_Stocks, USA_Gas_Stocks, ΔUSA_Ref_FUT, ΔWTI_Comm_net , US_Treas_6m_ps	ΔDest_Stocks_Eur, Crude_Stocks_Eur, ΔUS_Treas_Spread_1y_3m
3 lags	z_1, ΔWTI_front_mth, ΔOPEC_Spare, ΔDest_Stocks_Eur, ΔUSA_Crude_Stocks, USA_Gas_Stocks, ΔUSA_Ref_FUT, Δ2_US_Treas_6m_ps	Crude_Stocks_Eur, ΔWTI_Noncomm_net, ΔUS_Treas_Spread_1y_3m
	z_1, ΔWTI_front_mth, ΔOPEC_Spare, ΔDest_Stocks_Eur, ΔUSA_Crude_Stocks, USA_Gas_Stocks, ΔUSA_Ref_FUT, Δ2_US_Treas_6m_ps	Crude_Stocks_Eur, ΔWTI_Comm_net , ΔUS_Treas_Spread_1y_3m
	z_2, ΔWTI_front_mth, ΔOPEC_Spare, ΔDest_Stocks_Eur, ΔUSA_Crude_Stocks, USA_Gas_Stocks, ΔUSA_Ref_FUT, Δ2_US_Treas_6m_ps	Crude_Stocks_Eur, ΔWTI_Noncomm_net, ΔUS_Treas_Spread_1y_3m
	z_2, ΔWTI_front_mth, ΔOPEC_Spare, ΔDest_Stocks_Eur, ΔUSA_Crude_Stocks, USA_Gas_Stocks, ΔUSA_Ref_FUT, Δ2_US_Treas_6m_ps	Crude_Stocks_Eur, ΔWTI_Comm_net, ΔUS_Treas_Spread_1y_3m
	z_3, ΔWTI_front_mth, ΔOPEC_Spare, ΔDest_Stocks_Eur, ΔUSA_Crude_Stocks, USA_Gas_Stocks, ΔUSA_Ref_FUT, Δ2_US_Treas_6m_ps , ΔUS_Treas_Spread_1y_3m	Crude_Stocks_Eur, ΔWTI_Noncomm_net
	z_3, ΔWTI_front_mth, ΔOPEC_Spare, ΔDest_Stocks_Eur, ΔUSA_Crude_Stocks, USA_Gas_Stocks, ΔUSA_Ref_FUT, Δ2_US_Treas_6m_ps , ΔUS_Treas_Spread_1y_3m	Crude_Stocks_Eur, ΔWTI_Comm_net
4 lags	z_1, ΔWTI_front_mth, ΔOPEC_Spare, ΔDest_Stocks_Eur, ΔUSA_Crude_Stocks, USA_Gas_Stocks, ΔUSA_Ref_FUT, ΔWTI_Noncomm_net, Δ2_US_Treas_1y_py	Crude_Stocks_Eur, ΔUS_Treas_Spread_1y_3m
	z_1, ΔWTI_front_mth, ΔOPEC_Spare, ΔDest_Stocks_Eur, ΔUSA_Crude_Stocks, USA_Gas_Stocks, ΔUSA_Ref_FUT, ΔWTI_Comm_net, Δ2_US_Treas_1y_py	Crude_Stocks_Eur, ΔUS_Treas_Spread_1y_3m
	z_2, ΔWTI_front_mth, ΔOPEC_Spare, ΔDest_Stocks_Eur, ΔUSA_Crude_Stocks, USA_Gas_Stocks, ΔUSA_Ref_FUT, ΔWTI_Noncomm_net , Δ2_US_Treas_1y_py	Crude_Stocks_Eur, ΔUS_Treas_Spread_1y_3m
	z_2, ΔWTI_front_mth, ΔOPEC_Spare, ΔDest_Stocks_Eur, ΔUSA_Crude_Stocks, USA_Gas_Stocks, ΔUSA_Ref_FUT, ΔWTI_Comm_net , Δ2_US_Treas_1y_py	Crude_Stocks_Eur, ΔUS_Treas_Spread_1y_3m
	z_3, ΔWTI_front_mth, ΔOPEC_Spare, ΔDest_Stocks_Eur, ΔUSA_Crude_Stocks, USA_Gas_Stocks, ΔUSA_Ref_FUT, ΔWTI_Noncomm_net , Δ2_US_Treas_3m_pm	Crude_Stocks_Eur, ΔUS_Treas_Spread_1y_3m
	z_3, ΔWTI_front_mth, ΔOPEC_Spare, ΔDest_Stocks_Eur, ΔUSA_Crude_Stocks, USA_Gas_Stocks, ΔUSA_Ref_FUT, ΔWTI_Comm_net , Δ2_US_Treas_3m_pm	Crude_Stocks_Eur, ΔUS_Treas_Spread_1y_3m

Note: ΔX denotes 1st difference of X; Δ2_X is the 2nd difference of X. Source: Author´s estimates

4.3. VARXs Analysis

4.3.1. Impulse-Response Functions

In this subsection and in the next (4.3.2) we discuss the results of VARX estimation in terms of impulse-response functions and variance decompositions for z_1, z_2, and z_3 for each model. Recall that in the previous subsection (4.2), we have determined the sets of endogenous and exogenous variables that are part of each VARX model.

With this in mind, we have estimated 24 VARXs and have generated an equal number of impulse-response sets (one function for each endogenous variable) and variance decomposition sets using Cholesky decomposition to identify these functions.[24] Figures A.1 – A.12 in appendix A present impulse-response functions for these VARXs and the corresponding Cholesky decompositions.

It is also important to notice that each VARX satisfies the stability condition (i.e. all roots of the characteristic polynomial are inside the unit circle), which means that impulse-response functions are well behaved, decaying to zero after a certain point in time.[25]

Due to limited space, we report only the impulse-response functions for PCs (z_1, z_2, and z_3), and variance decompositions for PCs and WTI first month contract. Also, since results for Δ*WTI_Noncomm_net* and Δ*WTI_Comm_net* are quite similar, only the impulse-response functions and variance decompositions for the first variable are presented here.[26] The discussion which follows takes place regardless of whether PCs´ responses to shocks in one or more variables are significant or not (considering a 95% confidence interval). This is so because due to the exploratory nature of this work, we choose to analyse all responses of z_1, z_2, and z_3 to impulses in the relevant variables in order to better understand the different ways that they may affect WTI term structure.[27]

<u>Z1 (level)</u>

Since our impulse-response functions show that there is no contemporary effect from fundamental variables on z_1 (z_2 or z_3), all analyses which follow refer to responses from z_1 (z_2 and z_3) to past shocks (or future responses to present-week shocks, if you always consider the date they occur as the current time).

If we look to impulse-response functions for z_1 VARXs with one, two, three, and four lags, it is easy to see that as we move back in time (i.e. the number of lags in each VARX increases), some variables which have little or no effect on z_1 (the level of the futures curve) appear to gain some importance in explaining its behavior, while others become less relevant. It happens through a greater impact on z_1 (which can be checked by eye) or by inclusion (exclusion) in (from) the set of endogenous variables. A similar picture emerges for z_2 and z_3.

For Δ*OPEC_Spare*, for example, it is possible to notice its importance in explaining z_1 grows when more lags are added to the model. Its major (negative) impact on z_1 occurs at lag 3 (of the response functions), regardless as to whether the estimated model has 3 or 4 lags. So, in this case, an increase in OPEC spare capacity causes a downward change in the level of WTI future curve (z_1), as would be expected.

A positive change in Δ*WTI_front_mth* has a positive impact on z_1, which can be seen as evidence that the behavior of WTI spot price 'explains' part of the WTI futures level, at least in week two (lag 2).[28] It happens for all models (1, 2, 3, or 4 lags). A similar thing happens to Δ*WTI_Noncomm_net* (but only for models with one or two lags), with this variable being the factor with major importance in the second week. But, its impact fades out as we depart from the time when the shock occurs.

[24] In the present case, the Cholesky ordering assumes that the first (endogenous) variable is affected by contemporaneous shocks in all remaining (endogenous) variables, the second one is affected by (contemporaneous) shocks in the remaining variables less the first variable, and so on. It means that matrix *S* is upper triangular. For a discussion about VAR identification, see Enders (2004), and Hamilton (1994),

[25] For more details about this condition, see ibid.

[26] It does not mean that we believe noncommercial agents (or financial speculators) are important in explaining crude oil price behavior. Far from this, this question is not in the scope of this work. Personally, the author does not think financial speculation in crude oil markets may be a good explanation for crude price levels. A paper of mine about this point regarding the 2003-2007 period is Cavalcante (2008).

[27] PC´s responses lags which are statistically significant (at 95%) are identified in the figures presented in appendix A by colored dots.

[28] In terms of impulse-response functions of Δ*WTI_front_mth* (not shown here), a positive shock of one standard deviation in z_1 leads to the strongest response from Δ*WTI_front_mth* at lag 1 for all VARXs, with this effect fading out only after lag (week) 5 for VARXs with 1 and 2 lags, and after lag (week) 10 for VARXs with 3 and 4 lags. It suggests that the causal relationship between these variables may be bidirectional. However, it will become clear in the variance decomposition discussion (subsection 4.3.2) that shocks in z_1 have much stronger effects on Δ*WTI_front_mth* than vice-versa.

The US Treasury Rates (*Δ2_US_Treas_6m_ps* and *Δ2_US_Treas_1y_py*) appear to gain some importance for VARXs with 3 and 4 lags, when a positive shock in this variable has a negative impact on z_1 in the first two weeks, and then reverse to a positive one (the biggest in absolute value) during third and fourth weeks. From the fifth week on, it starts to decrease. The negative effect of this on z_1 is according to what we would expect from this variable (since an increase in interest rates should reduce oil demand, and then crude oil prices). But, the eventual positive response of z_1 to a positive impulse in interest rates (as in lags 3 and 4 of our impulse-response functions) may look puzzling, unless we interpret this as an increase in the cost of carrying a barrel of crude oil into the future.[29]

Positive impulses on distillate stocks in Europe (*ΔDest_Stocks_Eur*), and crude oil stocks (in the USA and Europe), all have negative impacts on z_1, as expected, which is clearer as more lags are included in VARXs. For refining utilization rate in the US (*ΔUSA_Ref_FUT*), the impulse-response functions show a consistent picture for week three forward (i.e. a higher products demand increases FUT, which augments crude oil demand and the price of the commodity).

Finally, about motor gasoline, which was the main oil product consumed in the US during 2002-2009, a positive shock in its stocks (*US_Gas_Stocks*) results in a negative response from z_1 for the first four weeks (as we should expect), but a positive one after week four – this effect fades out after week 15 (not shown in the charts). A possible explanation for this fact may be related to refinery planning, since an increase in gasoline stocks in the US usually occurs when its refining sector expands its gasoline output to meet expected demand for weeks or months ahead. So, in this case, a planned increase in stocks means higher crude oil demand and prices, at least in theory.

Z2 (stepness)

For z_2 VARXs (impulse-response functions for models with 1, 2, 3, and 4 lags), a positive shock in *ΔWTI_front_mth* has also the main response from z_2 (steepness) in the second week for all models. But, this response decreases fast, getting close to zero from lag 4 onwards.

Similarly to the z_1 case, a shock in *ΔWTI_Noncomm_net* is one of the major factors explaining z_2 responses in week 2 (for models with 1 and 2 lags), with a smaller response in week 3 (and opposite in sign). But, since z_2 refers to the steepness of WTI futures curve, a positive response for a positive impulse in a variable X, for example, means that the WTI term structure gets flatter (stepper) for contract-months 1 to 4 (5 to 12) as strong as the response from a given impulse is. So, a positive shock in *ΔWTI_Noncomm_net* reduces the slope of WTI futures curve (or makes it flatter) in week 2 for contract-months 1 to 4, and does the opposite in week 3.

The reason behind it may be that an increase in the noncommercial (or commercial) net positions in WTI futures (and options markets) helps to flatten the beginning of the curve (in week 2), since it may reduce the timespread (i.e. the difference between two prices along the curve). It can be interpreted as an indicative that the market believes (expects) the size of an increase (or decrease) in prices that may happen in the months following the first month is getting smaller.[30]

A positive impulse in *ΔUSA_Crude_Stocks* results in a positive response from z_2 for lags 2 and 3 for all VARXs, with varying degrees of importance. It is probably due to the presence of a contango structure in WTI futures markets, as it was the case for at least half of the time (weeks) between 2002 and 2009. But, for

[29] To see this point, use the following expression $F_t = S_t e^{(r+\mu-\rho)*(T-t)}$, where F_t is futures price of crude oil at time t for delivery at T, S_t is the spot price of crude oil at time t, r is the interest rate, μ is the storage cost (per barrel), ρ is the convenience yield, and T is the delivery date. So, an increase in r requires, by the non-arbitrage condition, an increase in F_t (or in z_1), *coeteris paribus*.

[30] According to the definition of timespread given in the text, it is not difficult to see that $timespread = h(z_2, z_3)$, where z_2 and z_3 are steepness and curvature PCs, with $h_2 > 0$ and $h_3 < 0$. This is so because the size of timespread does not depend on the level (z_1) of the futures curve.

lag 4 we got a negative response for VARXs with 2, 3, and 4 lags.[31] Note that *Crude_Stocks_Eur* is relevant only for a VARX with 1 lag, having a pattern of response similar to Δ*USA_Crude_Stocks*.

For Δ*USA_Ref_FUT*, z_2´s response is positive in lags 2 through 5 (in most cases) for all models, which can be understood with the following reasoning: an increase in FUT (probably due to a higher demand for oil products either by final consumers or for storage) leads to a downward (upward) move in price expectations, which causes a decrease (an increase) in the slope of crude futures curve for contract-months 1 to 4 (5 to 12). A possible explanation for this may be related to the perception that the market is probably well supplied of oil products for the near term, but maybe not for more distant months. [32]

In the case of *USA_Gas_Stocks*, z_2´s response is negative in lag 2 for all models (in this case, VARXs with 2, 3, and 4 lags), but with opposite signs for lag (week) 3 according to the VARX. However, contrary to the previous case (z_1), this variable does not seem to be of great relevance in explaining z_2´s behavior.

For Δ*OPEC_Spare*, z_2´s response is positive for almost all cases for lags 1 through 6, but with small absolute values in comparison to other variables. In theory, a positive z_2´s response from a positive shock in Δ*OPEC_Spare* is according to what we should expect, since, by Figure 3 (correlation loadings for WTI), an increase in OPEC´s spare capacity leads to a decrease (an increase) in futures curve´s steepness for lags 1 through 4 (from lag 5 on). The reasoning here is that a higher spare capacity reduces the risk of a crude supply scarcity for a given demand, which causes a downward adjustment in price expectations for months following the front month.

A positive shock in interest rates (Δ*2_US_Treas_6m_ps* and Δ*2_US_Treas_1y_py*) show mixed results (responses) from z_2 (for VARXs with 2, 3, and 4 lags) as we consider a specific lag in a given impulse-response function. For example, for the VARX with 2 lags, z_2´s response alternate in sign as we go back in time (weeks), being positive for weeks 2, 4, 7 and 8, and negative for week 3, 5, and 6. A similar thing happens to VARXs with 3 and 4 lags.

This evidence should be considered, keeping in mind the correlations loadings for z_2. So, for the 1st, 2nd, 3rd, and 4th WTI contract months, a positive (negative) response from a positive impulse in interest rates tends to reduce (increase) the slope of WTI futures curve for these months. But, for the 5th to 12th contract month, a positive shock in Δ*2_US_Treas_6m_*ps or Δ*2_US_Treas_1y_py* leads to an opposite response from z_2 in comparison to the previous case. The interpretation of these results is the same as for z_1.

Z3 (curvature)

Taking z_3´s impulse-response functions of VARXs models (with 1, 2, 3, and 4 lags), we see that a positive shock (of one standard deviation) in Δ*WTI_front_mth* results in mixed responses from z_3 (curvature) in weeks 1, 2, 3, 4, and 5, regardless of the model for which the response function is analyzed. For example, in week 3, the response is positive for models with 2, 3, and 4 lags, and negative for the VARX with 1 lag. We have similar cases in weeks 4, 5, and 6 (but not necessarily in the same order), to mention some of them.

Besides this, we can also notice that the strongest responses (in absolute values) from z_3 to a positive shock in Δ*WTI_front_mth* occur in weeks 2, 3, and 5, for VARXs with 1, 2 and 3, and 4 lags, respectively. These responses are negative for the first case and positive for the other cases, all with fast decay to zero after lag 5 (exception: VARX with 4 lags). Recalling Figure 3, this evidence can be combined with z_3's correlation loadings, allowing to conclude that a positive shock in Δ*WTI_front_mth* results in an increase in

[31] A contango (backwardation) term structure for crude oil is normally associated with an increase (a decrease) in the level of stocks for this commodity. So, since a positive shock in crude stocks in week t results in a positive response from the stepness factor (z_2) two or three weeks later, it can be interpreted as a move "toward backwardation" through flattening the futures curve in the first two or three months. This is so because market agents think the crude oil stocks may be far above normal (historical) level for these months, but not for following months, which is consistent with z_2 responses in lags 4 and 5. (see figures 3, and A.5-A.8).

[32] We do not assume here that futures price is an unbiased forecast for spot price in the future. It has been well established in the relevant literature that this is not the case for crude oil (and many financial assets). The only thing that can be said about this is that futures price may contain relevant information about market expectations for the spot price in the future, and that they usually change in the same direction.

the curvature of the term structure two weeks after the shock (for contract-months 2 to 7) followed by a decrease in it 3 and 5 weeks later (probably, as a way to counterbalance part of the first effect).

Notice that for WTI contracts from 8th to 12th month, a positive one standard deviation shock in the mentioned variable reduces the curvature of the WTI futures curve 2 weeks after it, and augments it 3 and 5 weeks later.

In the case of Δ*WTI_Noncomm_net*, which has the biggest response from z_3 in lag 2 for a positive shock in this variable (VARXs with 1, 2, and 4 lags), its negative response can be interpreted in a fashion similar to Δ*WTI_front_mth*: a positive shock leads to an increase in WTI term structure curvature from 2nd to 7th month, and a reduction in the following months (which augments as closer to the back of this curve one gets). It suggests noncommercial (commercial) agents may be taking positions "according to the curve", probably as a way to hedge themselves against unexpected price changes, or simply make profits. On the other hand, their positioning in the futures (and options) market certainly reveals relevant information about their expectations. Then, according to this view, changes in WTI term structure curvature can be rather a consequence of changes in perceptions about the future evolution of market fundamentals rather than motivated by pure speculation (see footnote 30 and the related discussion about timespread).

Responses to shocks in crude oil stocks in Europe (*Crude_Stocks_Eur*) and in the US (Δ*USA_Crude_Stocks*) are opposite in sign at lag 2 for VARX with 1 lag (*Crude_Stocks_Eur* is not an endogenous variable in VARXs with 2, 3, and 4 lags; see table 7), with both decaying to zero after lag (week) 4 (from lag 3 on, z_3´s responses to positive shocks in both variables are positive). If you consider Figure 3, we have the following: an increase (a positive shock) in Δ*USA_Crude_Stocks* augments WTI term structure curvature (i.e. in terms of a sphere, the plane which covers it become more stretched) at lag 2 (two weeks later) for contract-months 2 to 7, doing exactly the opposite in case of a positive shock in *Crude_Stocks_Eur* (for contract-months 8 to 12 the mentioned shock produces the converse result).

So, in the case of Δ*USA_Crude_Stocks*, this evidence may be interpreted as a consequence of a downward adjustment in the very short-term price expectations due to a higher level of crude stocks, and that market agents (at week 3) expect an increase in crude price expectations in the following weeks (so, they stock more crude oil).

In this fashion, we may say that Europe precedes the US, since a positive shock in *Crude_Stocks_Eur* results in a WTI futures curve "less stretched" in all weeks after the shock. It points to the fact that an increase (decrease) in crude stocks in Europe may be interpreted (in the US) as a market signal about an upward (downward) in crude oil prices in the near future.

For VARXs with more than 1 lag, all responses in lag 2 for a positive shock in Δ*USA_Crude_Stocks* are negative, and alternate in sign according to the VARX and to the number of weeks (lags) after the shock, all responses going to zero after week 8. These cases can be interpreted in a way similar to VARX with 1 lag.

In terms of Δ*OPEC_Spare*, impulse-response results for VARXs with 2, 3, and 4 lags show that a positive shock in this variable leads to a negative response from z_3 in lag 2, which turns positive or negative from lag 3 to 6, 10, and 11 depending on the VARX. From lag 7 to 9, z_3´s responses are negative for all cases and positive after lag 12 (albeit very small) for VARXs with 3 and 4 lags (they are negative for the VARX with 2 lags). With exception of lag (week) 2, these somewhat mixed results suggest that WTI term structure curvature reacts in different ways to a positive shock in Δ*OPEC_Spare* according to the time horizon one considers (e.g. the number of lags in each VARX).

For Δ*Dest_Stocks_Eur*, which is not an endogenous variable in the VARX with 2 lags (table 7), z_3´s responses to a one standard deviation impulse are positive in lags 2 and 3 for all VARXs (1, 3, and 4 lags), but are negative (positive) from lag 4 to 11 for VARXs with 3 and 4 lags (for the VARX with 1 lag). In terms of WTI term structure, the mentioned shock will cause a decrease in its curvature (term structure) for contract-months 2 to 7, 2 and 3 weeks after it happens, having the opposite effect 4 or more weeks later (at least in the case of VARXs with 3 and 4 lags). For contract-months 8 to 12, that shock will have the opposite effect.

This can be interpreted in exactly the opposite way we did for the case of z_3´s response to a shock in Δ*USA_Crude_Stocks*. The difference is probably related to the distinct ways crude oil and oil product stocks are treated during refinery planning.

In the case of *USA_Gas_Stocks*, z_3´s responses to an impulse in this variable vary according to the number of lags one adds to a VARX (2, 3, or 4 lags), showing no clear pattern in terms of sign, except that their impulse-response functions go to zero after lag 9. Since these mixed results may result in different interpretations due to distinct views and personal judgments, we prefer to leave it to the reader.

Responses from z_3 to impulses in Δ*USA_Ref_FUT* are negative in lag (week) 2 for VARXs with 2, 3, and 4 lags (they are positive for the VARX with 1 lag), and positive for lags 3 and 4 for most VARXs (exception: lag 4 for the VARX with 4 lags). From lag (week) 6 on, z_3´s responses are more negative than positive, getting close to zero after lag 7. In this case, a negative (positive) response from z_3 to a positive shock in Δ*USA_Ref_FUT* leads to an increase (decrease) in WTI`s futures curvature for contract-months 2 to 7, and at the same time to a decrease (increase) for front-month and 8 to 12 contract-months.

Finally, for Δ*2_US_Treas_6m_ps* and Δ*2_US_Treas_3m_pm*, a positive shock in interest rates leads to negative responses from z_3 in lag 2 and positive responses in lag 3 for VARXs with 2, 3, and 4 lags. From lag 4 on, responses differ in sign depending on the number of lags added to each VARX, but tend to decay to zero after lag 7. These results suggest that an increase in interest rates in week *t* leads to an increase in WTI term structure curvature (for contract-months 2 to 7) in week *t+2*, while one week later (*t+3*) the response for this shock is a decrease in that curvature (these results are the opposite for contract-months 8 to 12). This can be interpreted as evidence that, in the very short-term (2 week after the shock), an interest rate increase causes a downward adjustment in crude oil price expectations which is stronger for months 3 and 4 than for months 2, 5, 6, and 7. However, one week later, market agents appear to make upward revisions in their expectations about crude oil price.

In the case of interest rate spreads (Δ*US_Treas_Spread_1y_3m*), which is endogenous only for the VARX with 3 lags, a positive shock in Δ*US_Treas_Spread_1y_3m* brings positive responses from z_3 in lags 2, 5 to 7, and negative responses for lags 3, 4, and 8 to 11 (being positive after lag 14, which is not shown in figure A.11). Despite a relatively strong response in lag 6, the impulse-response function goes to zero after lag 4. Since this variable may be seen as an indicator of how tightening the monetary policy can be in the short-term in relation to the medium-term, its interpretation is similar to the case of interest rates.

4.3.2. Variance Decomposition

In this subsection we discuss briefly the results of the VARXs in terms of variance decompositions for the PCs (z_1, z_2, and z_3). As in the case of impulse-response functions, we use Cholesky factorization to decompose the variance of each endogenous variable for all VARXs, given a shock in each one of these variables.

For almost all cases, variance decompositions show that the endogenous variables z_2 and z_3 are responsible, for the most part, for their own variances (e.g. something between 80 and 100% at lag 20), which are also the only significant results (exception: *Crude_Stocks_Eur* for z_2 in a VARX with 1 lag), considering a 95% confidence level for a Chi-Square statistic with 415 degrees of freedom. So, we report here only the results for z_1 and Δ*WTI_front_mth*, which are by far the most interesting of this analysis. (Figures B.1 – B.4 in appendix B present variance decompositions for z_1 and Δ*WTI_front_mth* for VARXs with 1, 2, 3, and 4 lags)

For example, if you compare figures B.1 and B.2, it is easy to see that an innovation in z_1 has a much stronger effect on z_1´s variance than a shock in Δ*WTI_front_mth*, regardless the VARX has 1, 2, 3, or 4 lags. In fact, an innovation in the first variable accounts for between 76% and 90% at lag 20, leaving the difference for the remaining variables (Δ*WTI_front_mth* included).

When we look to the effect of shocks on Δ*WTI_front_mth* (Figures B.3 and B.4), the pattern is somewhat similar to the previous case, with something between 67% and 80% of the Δ*WTI_front_mth´s* variance at lag 20 being explained by an innovation in z_1. In this case, a shock in Δ*WTI_front_mth* is able to explain only 8%-11% of its own variance.

These apparently striking results can be easily understood if we consider them as evidence that WTI term structure has a stronger influence on spot prices (e.g. Δ*WTI_front_mth*) than our intuition suggests at first sight. In fact, since crude oil is not a commodity for instant delivery, it becomes natural to think of crude oil markets as a place where most transactions occur considering not current prices, but prices in the future. It suggests that crude oil prices should be observed in the context of futures markets, not alone. This idea is also helpful to explain the importance of Δ*WTI_front_mth* in the impulse-response analyses of subsection 4.3.1.

5. Conclusions

In this paper we discussed the different ways oil market fundamentals may affect crude oil pricing in the WTI futures market. Using different sets of fundamental variables (which are treated as endogenous or exogenous according to the model we estimate), it is shown that, for most cases, changes in the WTI term structure in 2002-2009 can be explained by changes in one or more of the aforementioned market fundamentals within this period. Also, responses to one standard-deviation impulses for different sets of endogenous and exogenous variables show consistent results for most cases. In other cases, an apparent inconsistency or puzzling result can be solved by using an alternative explanation (ex. interest rates and the cost of carrying).

In addition, we show that crude oil markets should be analysed considering not a single point in time, but the time span around the relevant date when a specific transaction takes place. In other words, since for many cases *WTI_front_mth* was an important variable in explaining the WTI term structure behavior, it suggests that crude oil spot price should be observed in the context of futures markets, not alone (crude oil is not a commodity for instant delivery!).

Finally, it is possible to infer from our results that as we bring more information to a model (by adding more lags, for example), the dynamics of the relationships among the endogenous/exogenous variables changes. It points out to the existence of many different forms market agents may use to combine information to generate their expectations about the future.

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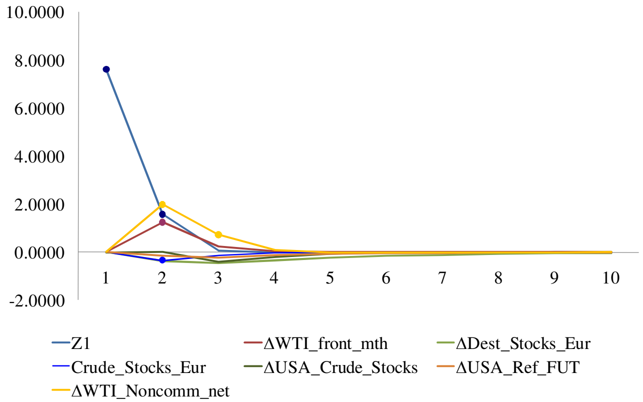
APPENDIX A

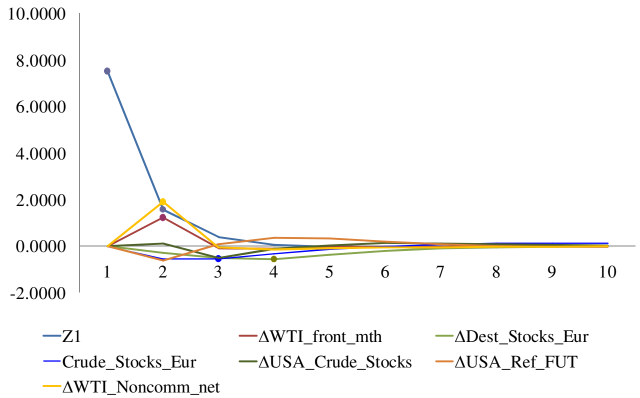
Impulse-Response Functions (Z1, Z2, Z3)

Figure A.1 - Impulse-Response for Z1 (1 lag)



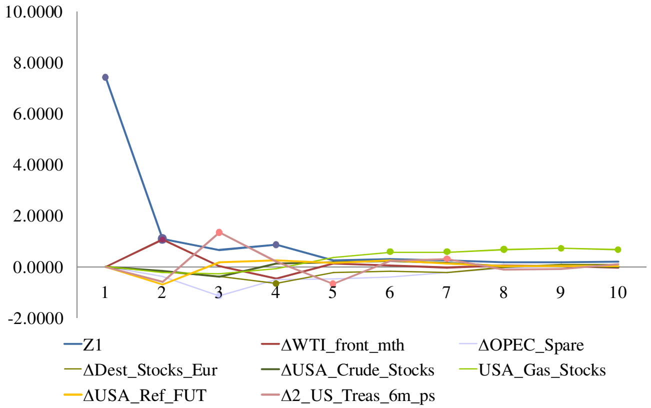
Cholesky Ordering: Z1, ΔWTI_front_mth, Crude_Stocks_Eur, ΔUSA_Crude_Stocks, ΔDest_Stocks_Eur, ΔUSA_Ref_FUT, ΔWTI_Noncomm_net

Figure A.2 - Impulse-Response for Z1 (2 lags)



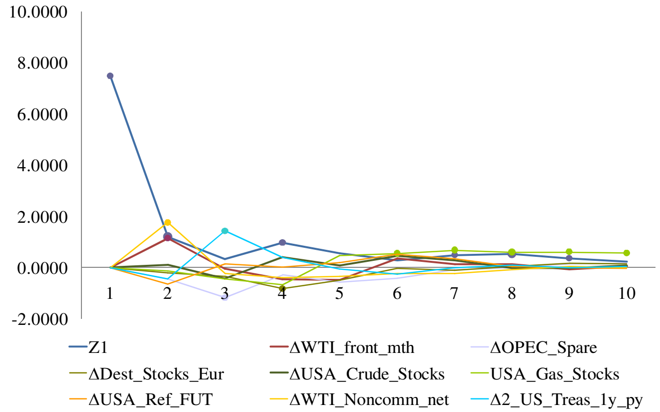
Cholesky Ordering: Z1, ΔWTI_front_mth, Crude_Stocks_Eur, ΔUSA_Crude_Stocks, ΔDest_Stocks_Eur, ΔUSA_Ref_FUT, ΔWTI_Noncomm_net

Figure A.3 - Impulse-Response for Z1 (3 lags)



Cholesky Ordering: Z1, ΔWTI_front_mth, ΔOPEC_Spare, ΔUSA_Crude_Stocks, USA_Gas_Stocks, ΔDest_Stocks_Eur, ΔUSA_Ref_FUT, Δ2_US_Treas_6m_ps

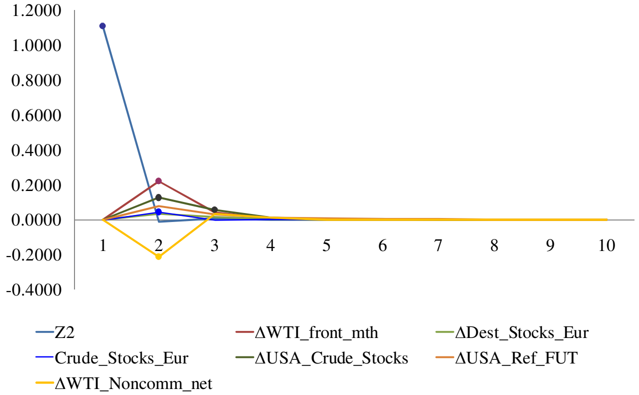
Figure A.4 - Impulse-Response for Z1 (4 lags)



Cholesky Ordering: Z1, ΔWTI_front_mth, ΔOPEC_Spare, ΔUSA_Crude_Stocks, USA_Gas_Stocks, ΔDest_Stocks_Eur, ΔUSA_Ref_FUT, ΔWTI_Noncomm_net, Δ2_US_Treas_1y_py

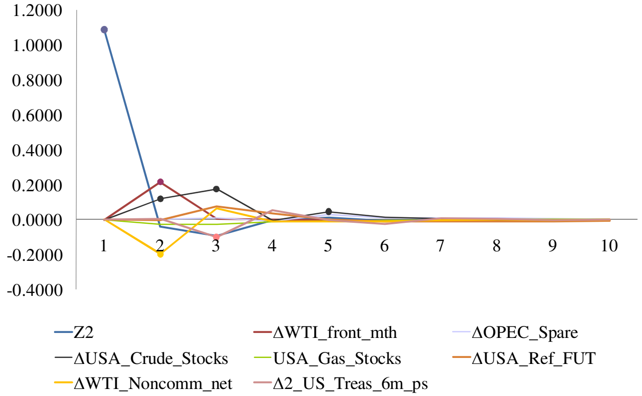
Note: Colored dots identify the statistically significant lags (at 95%) for each PC response to shocks of 1 standard deviation in a given variable.

Figure A.5 - Impulse-Response for Z2 (1 lag)



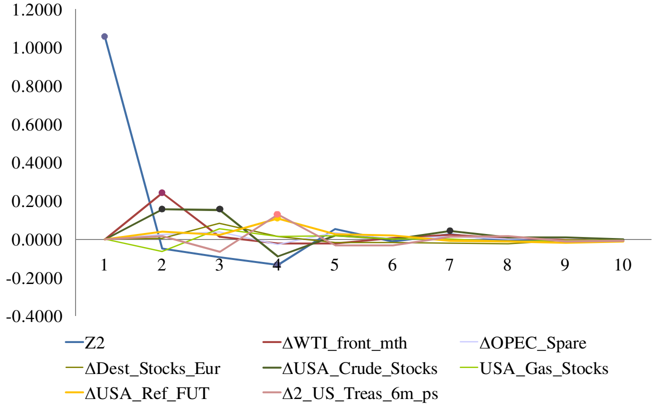
Cholesky Ordering: Z2, ΔWTI_front_mth, Crude_Stocks_Eur, ΔUSA_Crude_Stocks, ΔDest_Stocks_Eur, ΔUSA_Ref_FUT, ΔWTI_Noncomm_net

Figure A.6 - Impulse-Response for Z2 (2 lags)



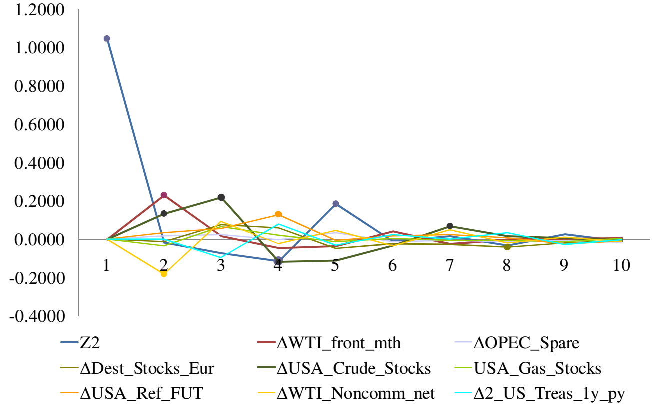
Cholesky Ordering: Z2, ΔWTI_front_mth, ΔOPEC_Spare, ΔUSA_Crude_Stocks, USA_Gas_Stocks, ΔUSA_Ref_FUT, ΔWTI_Noncomm_net, Δ2_US_Treas_6m_ps

Figure A.7 - Impulse-Response for Z2 (3 lags)



Cholesky Ordering: Z2, ΔWTI_front_mth, ΔOPEC_Spare, ΔUSA_Crude_Stocks, USA_Gas_Stocks, ΔDest_Stocks_Eur, ΔUSA_Ref_FUT, Δ2_US_Treas_6m_ps

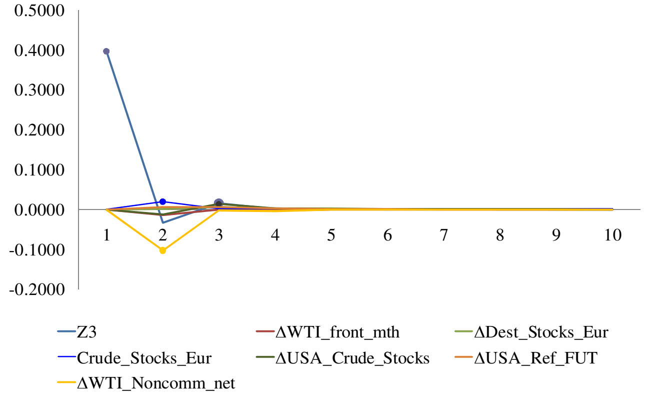
Figure A.8 - Impulse-Response for Z2 (4 lags)



Cholesky Ordering: Z2, ΔWTI_front_mth, ΔOPEC_Spare, ΔUSA_Crude_Stocks, USA_Gas_Stocks, ΔDest_Stocks_Eur, ΔUSA_Ref_FUT, ΔWTI_Noncomm_net, Δ2_US_Treas_1y_py

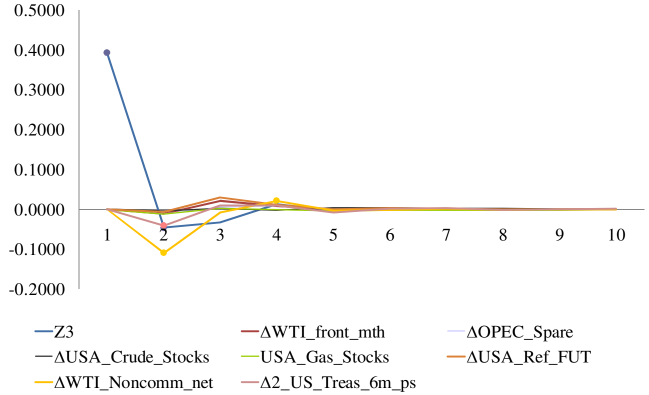
Note: Colored dots identify the statistically significant lags (at 95%) for each PC response to shocks of 1 standard deviation in a given variable.

Figure A.9 - Impulse-Response for Z3 (1 lag)



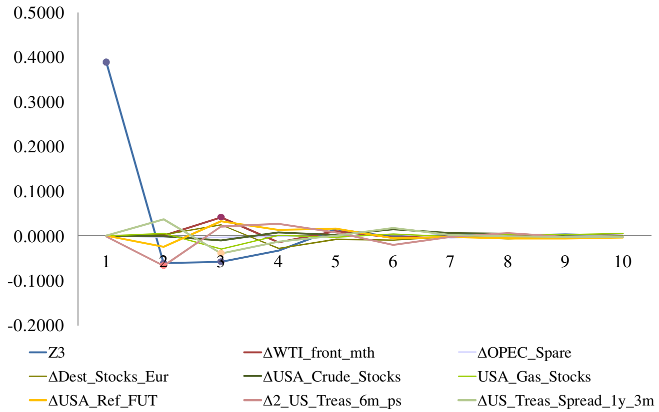
Cholesky Ordering: Z3, ΔWTI_front_mth, Crude_Stocks_Eur, ΔUSA_Crude_Stocks, ΔDest_Stocks_Eur, ΔUSA_Ref_FUT, ΔWTI_Noncomm_net

Figure A.10 - Impulse-Response for Z3 (2 lags)



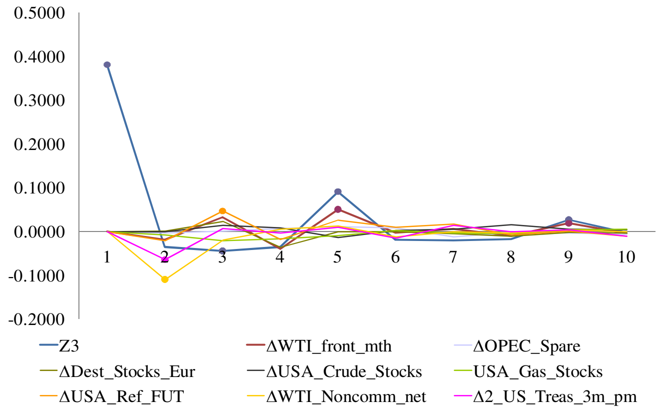
Cholesky Ordering: Z3, ΔWTI_front_mth, ΔOPEC_Spare, ΔUSA_Crude_Stocks, USA_Gas_Stocks, ΔUSA_Ref_FUT, ΔWTI_Noncomm_net, Δ2_US_Treas_6m_ps

Figure A.11 - Impulse-Response for Z3 (3 lags)



Cholesky Ordering: Z3, ΔWTI_front_mth, ΔOPEC_Spare, ΔUSA_Crude_Stocks, USA_Gas_Stocks, ΔDest_Stocks_Eur, ΔUSA_Ref_FUT, Δ2_US_Treas_6m_ps,ΔUS_Treas_Spread_1y_3m

Figure A.12 - Impulse-Response for Z3 (4 lags)



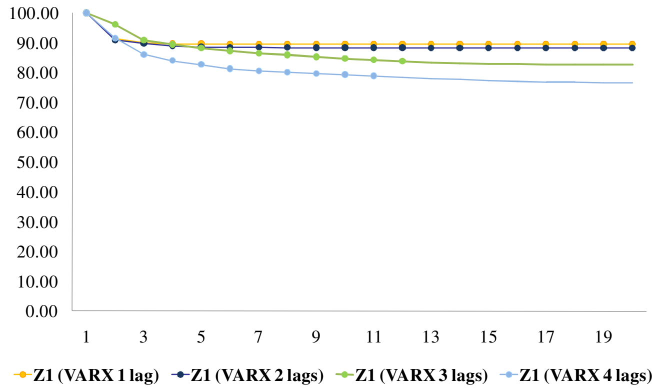
Cholesky Ordering: Z3, ΔWTI_front_mth, ΔOPEC_Spare, ΔUSA_Crude_Stocks, USA_Gas_Stocks, ΔDest_Stocks_Eur, ΔUSA_Ref_FUT, ΔWTI_Noncomm_net, Δ2_US_Treas_3m_pm

Note: Colored dots identify the statistically significant lags (at 95%) for each PC response to shocks of 1 standard deviation in a given variable.

APPENDIX B

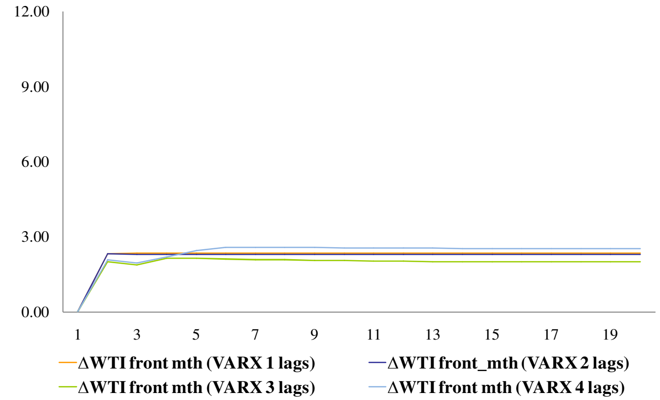
Variance Decomposition (Z1 & ΔWTI_front_mth)

Figure B.1 – Variance Decomposition for Z1 (Innovation in Z1)



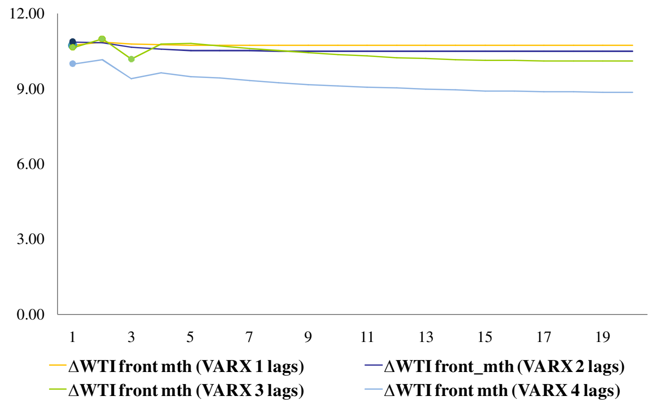
Cholesky Orderings: See Appendix A

Figure B.2 - Variance Decomposition for Z1 (Innovation in ΔWTI_front_mth)



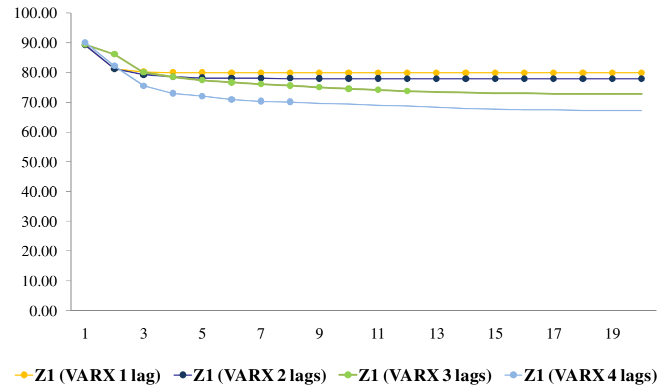
Cholesky Orderings: See Appendix A

Figure B.3 - Variance Decomposition for ΔWTI_front_mth (Innovation in ΔWTI_front_mth)



Cholesky Orderings: See Appendix A

Figure B.4 - Variance Decomposition for ΔWTI_front_mth (Innovation in Z1)



Cholesky Orderings: See Appendix A

Notes: Variance decomposition amounts are expressed in percentages (%). Colored dots identify the statistically significant lags (at 95%) for each variable (Z1 and ΔWTI_front_mth). Variances are chi-square distributed, with 415 degrees of freedom.