Psychological Barriers in Oil Futures Markets

Michael Dowling, Mark Cummins, Brian M. Lucey

Abstract

WTI and Brent futures are tested for the presence of psychological barriers around $10 price levels applying a multiple hypothesis testing approach for robustness. Psychological barriers are present in Brent pricing but not in WTI pricing, which is argued, based on recent behavioural finance research, to be due to the greater uncertainty inherent in Brent fundamental value determination. Particularly Brent displays significant resistance when breaching from below a $10 barrier level. Similar patterns are present at the $1 barrier level for the WTI-Brent spread. A range of reaction windows are applied with the main finding being that the trading potential around such psychological barrier levels is primarily in the immediate 1-5 days following a breach. The research contributes to the scant existing research on psychological influences on energy market traders, and suggests strong potential for further application of behavioural finance theories to improving understanding of energy markets pricing dynamics.

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1 Introduction

Recent research by Narayan, Narayan, and Popp (2011) investigates price clustering in oil futures and finds significant evidence of clustering in these contracts particularly around whole dollar amounts (i.e. prices with digits ending in .00). Further recent research by Bharati et al. (2012) finds clustering in whole dollar amounts ending in the 9 digit in NYMEX oil contracts. These findings contradict the notion of pricing efficiency, which would suggest that prices evolve in a manner where the likelihood of any given price change is approximately equal. This would in turn then result in the distribution of "trailing" digits (the last digit of a price) following either a uniform distribution of digits or a distribution following Benford's Law (see Bharati et al. 2012) and thus there being no systemic clusters of prices around digits. In contrast to this theory, a number of alternative price dynamic theories have been suggested, particularly a price attention and attractiveness hypothesis, developed based on psychological principles and empirical observations of trader and price behaviour, which suggests that traders pay particular attention to certain price points and are naturally drawn to whole number prices thus leading to price clustering. This clustering behaviour has been observed across a range of financial markets, including equity markets (Ikenberry and Weston, 2008; Bhattacharya et al. 2012), gold pricing (Aggarwal and Lucey, 2007) and carbon markets (Palao and Pardo, 2012).

In this paper we extend the price clustering testing in oil futures markets by testing for the presence of psychological barriers in pricing. Psychological barriers can be viewed as a partial explanation for clustering, as it is posited that prices cluster around certain digits due to trader's differential perspectives of prices around psychologically important price points such as whole dollar or tens of dollar prices, compared to non-psychologically important price points Mitchell (2001). An important advance on price clustering is that psychological barriers focuses on price directional movements around barrier regions and is thus of particular relevance to informing trading behaviour. Psychological barriers have been previously observed in equity markets (Ikenberry and Weston, 2008; Bhattacharya et al. 2012), and more relevantly, in markets primarily traded by professional traders, such as foreign exchange (Westerhoff, 2003) and gold (Aggarwal and Lucey, 2007).

Our study investigates the presence of psychological barriers in the pricing of WTI and Brent futures over the time period 1990-2012. This is motivated by the prior finding of price clustering in oil futures, given the aforementioned overlap between clustering and psychological barriers. The presence of psychological barriers in other markets primarily traded by professional traders provides a further impetus for the study. This research partially addresses the paucity of studies involving the application of psychological bias theories to energy futures markets, despite their widespread application in other financial markets. A traditional explanation for this lack of research is the view that psychological factors should mainly influence the investment decisions of small investors (usually in equity markets) who are most likely to be boundedly-rational in their decision making due to limited appropriate knowledge and limited ability to process that knowledge (DeLong et al., 1990). Given that energy futures are primarily traded by professional market participants there should be a limited role for psychological influences in their trading behaviour according to this perspective. This view has been challenged by recent studies on professional market participant studies. For example, intra-day trading patterns of Chicago Board of Trade (CBOT) traders show loss aversion influencing decision making (Coval and Shumway, 2005); the trading decisions of currency traders display overconfidence (O'Connell and Teo, 2009); and differences in testosterone levels (linked to risk taking) are associated with differences in trading profitability amongst professional traders (Coates and Herbert, 2008; and expanded in Coates, 2012). Thus it is unlikely that oil futures market participants will be immune to psychological bias influences on their trading behaviour.

More generally studies of price dynamics in energy markets remain relative sparse compared to equivalent studies in the financial markets. The reason for this is in no small part due to the very distinctive features of the energy markets, in particular the less than complete transparency of physical markets and the lack of liquidity for many derivatives contracts (Swierenga, 2012). A better understanding of price dynamics in energy markets is of interest to market participants, regulators and researchers, and this is motivated by the need to appraise the influence of exchange based and over-the-counter based trading activity on long-term physical contracts (Swierenga, 2012). Furthermore, the "financialization" of energy markets has become an ever-growing topic of interest for industry participants and academics alike. This is the central focus of a recent 2012 report from the United Nations Conference on Trade and Development, for instance. Increased financial trading activity and participation by financial market actors (such as institutional investors and hedge funds) has become a feature of energy and, more broadly, commodity markets in recent years. Much debate abounds on the extent and effect of speculative trading on energy markets, with increased research output on the topic (Tokic, 2011; Hache and Lantz, 2012). The examination, in this study, of psychological influences in energy prices adds in a unique way to the price dynamics literature, with the identified evidence of psychological barriers influencing pricing providing insights into speculative effects on price that deviate from the market fundamentals of supply and demand.

We significantly expand on the previous approaches to testing psychological barriers through a number of theoretical and testing advances that offer novel perspectives on how psychological barriers are likely to influence oil futures pricing. Focusing on $10 barrier regions (movements through a price ending in a 0 dollar digit) we show that psychological barriers only appear to influence prices in period 1990-2006 where prices traded at in a lower range of approximately $10-$78, relative to the 2007-2012 period . The choice to split the data at the 2006-2007 juncture is made to capture the peak in oil prices at $145/$146 per barrel in 2007 and the resulting collapse in oil prices from 2008 with the emergence of the credit crisis. The split is also driven by the finding of De Zwart et al. (2009) that when markets are strongly driven by fundamentals, as during the 2007-2012 oil market, traders tend to switch to fundamental pricing models, leaving minimal scope for influence from psychological barriers. Significant focus is also placed on determining the speed of market reaction to barrier breaches, with reaction time periods from 1 day to 2 weeks tested. This has traditionally been ignored in the psychological barriers literature but has important trading implications as to the profitability of any identified pricing patterns.

We further distinguish between WTI and Brent contracts on the grounds of uncertainty in determining fundamental value. Kao and Wan (2012) highlight the close relationship between WTI pricing and Cushing inventory levels, while Jin et al. (2012) demonstrate Brent's responsiveness to global price shocks and WTI's disconnect from such shocks. We argue that this suggests greater uncertainty in the pricing of Brent compared to WTI, due to the greater complexity inherent in pricing this global benchmark compared to what is increasingly becoming a US domestic inventory-driven market. Drawing on recent advances in behavioural finance showing an increased role for psychological biases in more complex decisions (e.g. Dowling and Lucey, 2008; Yao and Li, 2012) we therefore expect, and find, that the greater uncertainty surrounding Brent fundamental value leads to a greater role for psychological barriers in pricing for these contracts. We argue in the conclusions section that this uncertainty-driven perspective on psychological influences offers significant potential as a framework for future similar studies in energy markets. This conclusion emerges from our application of generalised multiple hypothesis testing approaches to minimise the potential for false discoveries in our testing framework - a problem commonly referred to as the *multiple comparisons problem* in statistical literature. Controlling for the multiple comparisons problem as we do in this study allows us to make robust conclusions on the psychological barrier effects in crude oil markets and forms a final key advancement of the literature.

2 Methodology and Data

The main testing approach is an adaptation of Aggarwal and Lucey (2007) and involves two groups of tests: (i) barrier tests, which are akin to price clustering analyses, and (ii) tests of conditional effects. Barrier tests consist of proximity and kurtosis tests. Barrier proximity tests examine whether digits close to a hypothesised psychological barrier show abnormal frequencies and thus act as a test of price clustering without necessarily investigating the prices around which clustering happens, while barrier kurtosis (also known as barrier hump) tests examine whether there is a significantly different frequency distribution around the numbers being investigated. Tests of conditional effects consider a range of possible different reactions to the particular barrier condition; e.g. whether a price is approaching a barrier point from below or above, and whether the price is approaching a barrier or whether the barrier has been passed. The barrier tests are described next and the tests of conditional effects are outlined in Section 2.2.

2.1 Barrier Tests: Evidence for Clustering

Barrier proximity tests are designed to measure whether or not price observations on or near barriers occur significantly less frequently than a uniform distribution would predict. In general, these tests examine the shape of the frequency distribution for various decimal digit combinations. The tests of this paper examine the presence of “10s” and “1s” psychological barriers. 10s psychological barriers test the two digits bracketing the decimal point and 1s tests examine the two digits to the immediate right of the decimal point. An expectation based on prior studies is that barriers are most likely to exist at exact tens of dollars, such as $100 for example, so there should be higher frequency in the 10s of 00 digits compared to other digits. A similar finding is expected around 00 digits in the 1s tests, which denotes whole dollar price amounts. For the barrier tests in this study, a barrier range is defined rather than applying the tests to a strict barrier of 00. The barrier ranges considered for study are set out below but taking the \$100.00 level for instance then then we are interested in prices that surround this level, such as \$99.8x, \$99.9x, \$100.1x and \$100.2x. Following the definition that the 10s barriers bracket the decimal point, the digit combinations of interest would be 98, 99, 01 and 02 respectively. Taking for instance a price level transition from \$103.xx to \$104.xx, we would be interested in prices such as \$103.98, \$103.99, \$104.01 and \$104.02. Following the definition of the 1s barriers as being the two digits to the immediate right of the decimal point, the digit combinations of interest would again be 98, 99, 01 and 02 respectively.

In this context, we define M to be the set of all digits $\{0, \ldots, 99\}$. Specifically, three barrier ranges are defined as follows: $BR^1 \equiv \{98, 99, 00, 01, 02\}$, $BR^2 \equiv \{95, \ldots, 00, \ldots, 05\}$ and $BR^3 \equiv \{90, \ldots, 00, \ldots, 10\}$, all of which are centred on 00. Each of the defined barriers is then represented by a dummy variable, D^i,$i = 1, 2, 3$, taking a value of 1 for digits in the barrier range and 0 otherwise, with the specific equation tested being:

$$f(M) = \alpha + \beta D^i + \varepsilon,$$

where $f(M)$ is the absolute frequency of digits. The test for barriers then resolves to a test of significance of the coefficient on the dummy variable. Under the null of no barriers will be zero, whereas the presence of barriers will result in a higher frequency of M-values at the barrier and thus will be positive and significant.

The barrier kurtosis tests examine whether there is a significantly different frequency distribution shape around the barrier points and takes the testing form:

$$f(M) = \alpha + \varphi M + \gamma M^2 + \varepsilon,$$

with the M-digits being regressed on both their values and the square of their values. If there is no abnormal distribution shape around barrier points then the coefficient of γ should have a value of 0, while the presence of an abnormal barriers shape would be suggested by a significant negative coefficient, while clustering would be shown in a significant positive coefficient.

2.2 Tests of Conditional Effects: Psychological Barriers

A range of possible conditional effects are further tested to determine if there is a differential reaction depending on the conditions related to the psychological barrier; such as whether the barrier is being approached by rising prices or by prices falling, or other relevant conditions that might conceivably influence reaction. An example of how condition can influence professional trader behaviour comes from **[9]**, who find that trader performance during a morning trading period influences risk attitudes and levels of loss aversion in afternoon trading sessions i.e. afternoon trading is conditioned on morning trading. Our initial test is an OLS regression with dummy variables based on whether barriers are (i) being approached or (ii) after being breached, and also whether a barrier is reached through rising or falling prices. This necessitates setting up of the following four dummy variables:

- BDB^n, which assigns 1 to the n days *before* a downward breach, i.e. a barrier breach from above due to *downward* or falling prices;
- ADB^n, which assigns 1 to the n days *after* a downard breach, i.e.a barrier breach from above due to *downward* or falling prices;
- BUB^n, which assigns 1 to the n days *before* an upward breach, i.e. a barrier breach from below due to *upward* or rising prices;
- AUB^n, which assigns 1 to the n days *after* an upward breach, i.e. a barrier breach from below due to *upward* or rising prices.

These dummy variables are regressed against returns in order to determine whether the periods covered by each dummy are associated with anomalous behaviour. Specifically, the following regression model is considered:

$$R_t = \beta_0 + \beta_1 R_{t-1} + \beta_2 BDB_t^n + \beta_3 ADB_t^n + \beta_4 BUB_t^n + \beta_5 AUB_t^n + \varepsilon_t. \quad (1)$$

To test the speed of market reaction to barrier breaches, we consider a range of reaction windows of size n days. Specifically, we choose $n = 1, 2, 3, 4, 5$ and 10 days, which allows us to assess the speed of market reaction over the week before and the week after a barrier breach but also, for comparative purposes, over a longer two-week period before and after a barrier breach. As we define a barrier breach to be any price reached above or below a given barrier threshold, the reaction windows allow us to explicity take account of false barrier breaches as we are looking to ascertain if patterns in price behaviour exist subsequent to barrier breaches.

2.3 Data Description

Front-month WTI (CME) and Brent (ICE) futures contracts are used for the analysis, representing the two key global benchmarks in the oil markets. The front-month contracts are used as they provide price information for the most actively traded contracts by volume.[1] The analysis provides interesting insights into psychological barrier effects into oil futures trading. We make the distinction between WTI and Brent contracts on the grounds of uncertainty in determining fundamental value, arguing that WTI pricing is closely tied to Cushing inventory levels and thus has relatively less ambiguity in determining fundamental value compared to the more complex determinants of Brent pricing. Drawing on recent advances in behavioural finance, we therefore hypothesize that the greater uncertainty around Brent fundamental value leads to a greater role for psychological barriers in pricing for these contracts. To extend the analysis further, the locational spread between WTI and Brent is also considered as part of the data set. This allows for an investigation into psychological barriers in the relative prices between these two key benchmarks. Table 1 provides descriptive statistics for the three data series.

[1]The futures contract with the largest open interest would likely reflect the contract with the most professional trader interest. The contract with highest open interest is typically the front-month contract and so this contract in general represents the highest levels of both volume and open interest. It is important to emphasise that the results of this paper relate to (front-month) futures prices for WTI and Brent and do not span the entire WTI and Brent futures curves or indeed the broader suite of physical and financial WTI and Brent prices. For the Brent complex, for instance, we do not conisder physical Dated Brent or Cash BFOE prices or other the prices of other financial products such as Contracts-for-Differences (CfDs) or Dated-to-Frontlines (DFLs). Such considerations are deferred for future research as set out in the conclusion.

	WTI	Brent	WTI-Brent Spread
Units	\$/bbl	\$/bbl	\$/bbl
Start Date	11/10/1990	11/10/1990	11/10/1990
End Date	10/10/2012	10/10/2012	10/10/2012
Mean	42.81	43.04	-0.24
Std Dev	29.3905	32.4088	5.0882
Skew	1.0348	1.1268	-3.0300
Kurt	2.9579	3.0697	11.8781
Max	145.29	146.08	6.53
Min	10.72	9.64	-27.88

Table 1: Data Descriptive Statistics

<< insert Figure 1 here >>

Figure 1: 10s Frequency Distribution

3 Empirical Results

To begin the empirical analysis, Figure 1 presents a radar chart of the 10s frequency distribution for WTI and Brent, while Figure 2 presents a radar chart of the 1s frequency distribution for WTI, Brent and the WTI-Brent spread. It is quite clear from the both plots that the 10s and 1s frequency distributions do not conform to the uniform distribution. So informally it would appear that price clustering may be a feature.

To examine this formally, the barrier tests set out in Section 2.1 are performed. Specifically, barrier proximity and barrier kurtosis tests are applied to the WTI, Brent and WTI-Brent spread series, with 10s and 1s psychological barriers being considered for the price series and 1s psychological barriers only for the spread series. The three barrier ranges defined in Section 1, i.e. $BR^1 \equiv \{98, 99, 00, 01, 02\}$, $BR^2 \equiv \{95, \ldots, 00, \ldots, 05\}$ and $BR^3 \equiv \{90, \ldots, 00, \ldots, 10\}$, are considered for the barrier proximity testing. Tables 2 and 3 report the barrier proximity and barrier kurtosis results respectively; significant results at the 1%, 5% and 10% levels are all bolded for convenience. From the barrier proximity results, there is strong evidence of price clustering effects around the 10s psychological barriers for

<< insert Figure 2 here >>

Figure 2: 1s Frequency Distribution

WTI in the case of all three barrier ranges. Indeed, the evidence suggests that the frequency of the barrier range digits is higher than the digits outside these regions by approximately 18, 19 and 14 observations for BR^1, BR^2 and BR^3 respectively. In addition to this, for the third barrier region, there is strong evidence of price clustering effects around the 10s barriers. The frequency of the barrier range digits in this case is higher than the digits outside the region by approximately 6 observations. In general, there is no evidence of 1s barriers price clustering for any of the series considered. Only in the case of the WTI-Brent spread, and only for the second barrier region, do price clustering effects emerge around the 1s barriers. The evidence points to a lower frequency of observations in this case of approximately 6 observations. From the barrier kurtosis tests, it can be seen that a statistically significant γ is reported for both WTI and Brent around the 10s psychological barriers. Indeed, the positive coefficient values provide evidence of price clustering for both crude oils.

Motivated by the price clustering evidence set out above, tests of conditional effects are next performed to determine whether there are differential reactions in the lead up to and subsequent to barrier breaches and whether these barrier breaches occur from above, i.e. due to falling prices, or from below, i.e. due to rising prices. The tests implemented are as described in Section 2.2. For WTI and Brent, \$10 barrier levels are considered over the range \$10-\$140, which spans the price levels achieved over the sample period. For the WTI-Brent spread series, \$1 barrier levels are considered over the range -\$27 - \$6, which spans the observed spread series. The negative barrier levels reflect the significant premium at which Brent has been trading to WTI over recent months. All barrier breaches are recorded and then the dummy variables BDB_t^n, ADB_t^n, BUB_t^n, AUB_t^n are constructed as set out in Section 2.2. To test for the market reaction to barrier breaches, we consider the range of reaction windows $n = 1, 2, 3, 4, 5$ and 10 days, which allows us to assess the speed of market reaction over the week before and the week after a barrier breach but also, for comparative purposes, over a longer two-week period before and after a barrier breach. Figure 3 provides histograms for the price levels at which barrier breaches occur, where the histogram bins have been centred on the respective \$10 and \$1 barrier levels. Table 4 provides a summary count of the downward and upward barrier breaches for subsample blocks of the data. Table 5 gives the results of the tests of conditional effects on WTI and Brent, while Table 6 provides the results for the WTI-Brent spread. Significant results at the 1%, 5% and 10% levels are all bolded for convenience.

Of most interest in the findings is the market reaction after a barrier breach, whether from above or from below. Hence, the coefficients for the ADB_t^n and AUB_t^n dummy variables provide important insights. It is first noted that the greatest evidence for psychological barrier effects exists in the case of Brent, with some evidence for such effects in the case WTI as well. In particular, for barrier breaches from above, Brent is shown to have on average a positive return effect over 2, 3, 4 and 5 days after the barrier breach, with no such evidence over the longer 10-day window. For WTI, a similar positive return effect is only seen for the 3-day reaction window. The positive return effects clearly point to these barriers providing general support to crude oil prices. The barriers are breached from falling prices and in response to these breaches prices tend on average to rise again. For barrier breaches from below, Brent again shows strong evidence of psychological barrier effects with statistically significant results emerging for all reaction windows, even the longer 10-day reaction window. WTI also shows increased evidence of psychological barrier effects in the case of barrier breaches from below. Market reactions are evidenced over the 2-, 4-, 5- and 10-day reaction windows. Notably, Brent and WTI are both shown to have on average negative return effects. These negative return effects indicate that the \$10 barriers provide general resistance to rising crude oil prices, showing that barrier breaches from rising prices tend on average to lead to falling prices subsequently. So, overall we find evidence for psychological barrier effects in both Brent and WTI prices, although more evidence exists for Brent compared to WTI. This points to a potential difference between Brent and WTI, which may be driven differences in these crude oil prices with greater uncertainty in determining the fundamental value in the case of Brent, while WTI is intimately linked to the Cushing inventory levels. We return to this idea in the next section where we re-examine the difference between WTI and Brent within the context of multiple hypothesis testing and the multiple comparison problem.

For the WTI-Brent spread series, the results set out in Table 6 show evidence as well of psychological barrier effects around the \$1 barrier levels. In particular, conditional effects can be seen to exist consistently across the 2-, 3-, 4-, 5- and 10- day reaction windows and for both barrier breaches from rising and from falling spread levels. Indeed, the signs of the reported coefficients for the ADB_t^n and AUB_t^n dummy variables are consistent with the WTI and Brent analysis above. The results point to general support in the case of barrier breaches due to falling spreads and general resistance in the case of barrier breaches from

Contract	10s			1s		
	β	p-value	R^2	β	p-value	R^2
Barrier Range 1: $\{98, 99, 00, 01, 02\}$						
WTI	**18.484**	**0.005**	**0.079**	-0.032	0.993	0.000
Brent	3.958	0.510	0.004	5.221	0.114	0.025
WTI-Brent Spread	N/A	N/A	N/A	-4.421	0.322	0.010
Barrier Range 2: $\{95, 96, \ldots, 04, 05\}$						
WTI	**19.199**	**0.000**	**0.176**	1.029	0.688	0.002
Brent	6.022	0.149	0.021	2.243	0.332	0.010
WTI-Brent Spread	N/A	N/A	N/A	**-5.781**	**0.061**	**0.035**
Barrier Range 3: $\{90, 91, \ldots, 09, 10\}$						
WTI	**14.440**	**0.000**	**0.169**	-1.340	0.495	0.005
Brent	**6.423**	**0.044**	**0.041**	0.817	0.646	0.002
WTI-Brent Spread	N/A	N/A	N/A	-3.291	0.167	0.019

Table 2: Barrier Proximity Tests

Contract	10s			1s		
	γ	p-value	R^2	γ	p-value	R^2
WTI	**0.014**	**0.000**	**0.557**	0.000	0.671	0.009
Brent	**0.004**	**0.004**	**0.432**	0.000	0.823	0.006
WTI-Brent Spread	N/A	N/A	N/A	-0.001	0.211	0.291

Table 3: Barrier Kurtosis Tests

rising spreads.

The sample period considered in this study spans the years from 1990-2012. The dynamics of the crude oil market changed significantly over this two-decade period. In particular, from 2006 up to 2008 crude oil prices experienced an unprecedented bull market run, with prices continuously reaching new record highs until 2008 when prices had reached levels just below $150 per barrel. Of course, in 2008 and leading into 2009, oil prices were seen to collapse back down to levels ultimately under $40 per barrel, driven by the credit crisis and the resulting global economic downturn that emerged. Of course, in recent years prices have

<< insert Figure 3; Tiled: Fig. 3(a) & 3(b) top panel; Fig. 3(c) bottom panel >>
* Figure 3(a) WTI, Figure 3(b) Brent, and Figure 3(c) WTI-Brent Spread.

Figure 3: Barrier Breaches: Histogram of Price Levels

WTI										
	1990-1994		1995-1999		2000-2004		2004-2009		2010-2012	
Barrier ($)	# Down	#Up	# Down	#Up	# Down	#Up	# Down	#Up	# Down	#Up
10	0	0	0	0	0	0	0	0	0	0
20	22	21	22	23	7	7	0	0	0	0
30	5	4	0	0	28	29	0	0	0	0
40	0	0	0	0	4	5	4	4	0	0
50	0	0	0	0	3	3	10	11	0	0
60	0	0	0	0	0	0	19	20	0	0
70	0	0	0	0	0	0	23	24	2	2
80	0	0	0	0	0	0	8	9	12	12
90	0	0	0	0	0	0	7	7	11	12
100	0	0	0	0	0	0	6	6	13	13
110	0	0	0	0	0	0	3	2	2	2
120	0	0	0	0	0	0	3	4	0	0
130	0	0	0	0	0	0	4	4	0	0
140	0	0	0	0	0	0	3	3	0	0

Brent										
	1990-1994		1995-1999		2000-2004		2004-2009		2010-2012	
Barrier ($)	# Down	#Up	# Down	#Up	# Down	#Up	# Down	#Up	# Down	#Up
10	0	0	2	2	0	0	0	0	0	0
20	24	23	15	16	6	6	0	0	0	0
30	3	3	0	0	22	23	0	0	0	0
40	0	0	0	0	5	6	3	3	0	0
50	0	0	0	0	3	3	7	8	0	0
60	0	0	0	0	0	0	17	18	0	0
70	0	0	0	0	0	0	23	24	2	2
80	0	0	0	0	0	0	3	3	7	8
90	0	0	0	0	0	0	11	11	1	2
100	0	0	0	0	0	0	4	4	7	8
110	0	0	0	0	0	0	1	1	19	20
120	0	0	0	0	0	0	2	2	5	5
130	0	0	0	0	0	0	3	3	0	0
140	0	0	0	0	0	0	3	3	0	0

Table 4: Barrier Breach Count for Subsample Blocks

gradually ticked back upwards to levels around the \$80, \$90 and \$100 mark. In view of this, the analysis above is extended by re-analysing psychological barriers effects for two sub-sample periods: 1990-2006 and 2007-2012. This allows us to consider whether there are differences in psychological barrier effects between the pre-credit crisis period of 1990-2007 and the credit crisis period from 2007 onwards. The results of the tests of conditional effects for these two sub-sample periods are provided in Appendix A. Significant results at the 1%, 5% and 10% levels are again bolded for convenience.

For the pre-2007 period, it can be seen that there is evidence for general support for oil prices when barrier breaches occur due to falling prices and that this is true for Brent over the 3-, 4-, 5- and 10-day reaction windows and for WTI only for the 3-day reaction window. Likewise, there is strong evidence for general \$10 barrier resistance in oil prices for both Brent and WTI across almost all reaction windows. For the WTI-Brent spread, support and resistance barriers are again shown to exist for almost all reaction windows considered. However, in complete contrast to these results that point to psychological barrier effects, when one moves to the post-2006 period, all of this evidence falls away for the crude oils themselves and for the spread. So it appears that during this unprecedented period of strong market direction in the oil markets, traditional psychological barriers that previously existed were dismissed by the market participants during the bull run up to 2008 and the subsequent bear retreat following the credit crisis. It is quite clear from this evidence that the oil markets followed and were driven by the general global economic boom and bust and that general support-resistance psychological barriers that had contained oil prices at lower prices levels collapsed over this period. This aligns with the findings of De Zwart et al. (2009) who argue that when markets are strongly driven by fundamentals, as during the 2007-2012 oil market, traders tend to switch to fundamental pricing models, leaving minimal scope for influence from psychological barriers.

4 Multiple Comparisons Problem

At this juncture, we raise an important limitation of the analysis conducted thus far. In particular, it is noted that the range of testing performed amounts to a large scale multiple hypothesis testing exercise. Specifically, between all of the barrier tests and the tests of conditional effects conducted on the full sample and the two sub-samples, a total of 369 coefficient hypothesis tests are performed. This introduces the well-established *multiple comparisons problem*. The multiple comparisons problem may lead to the identification of statistically significant results by pure chance alone when performing multiple hypothesis tests simultaneously. Without controlling for the multiple comparisons problem, the probability of rejecting true hypotheses, i.e. making *false discoveries*, is increased. Romano *et al.* (2010) provide a detailed exposition of the issues pertaining to multiple hypothesis testing (MHT), outlining the key literature in the area and in particular a range of generalised MHT techniques that have been developed to control for the multiple comparisons problem. This problem is well addressed in the scientific and medical fields but is largely ignored in the empirical finance, including the energy finance literature. Cummins (2013a) presents the argument to control for the multiple comparison problem via generalised MHT procedures within the context of analysing EU Emissions Trading Scheme emissions market interactions. Cummins (2013b) uses similar techniques for analysing interactions between emissions and energy markets. Cummins and Bucca (2012) examine the quantitative trading of oil market spreads, using generalised MHT techniques to robustly evaluate the performance of statistical arbitrage trading strategies.

By way of motivation for the reader, consider a simple experiment, as per Romano *et al.* (2010), whereby $n = 100$ simultaneous hypothesis tests are performed, all of which are assumed to be true. Taking a significance level of $\alpha = 5\%$, one would expect five of the true

Reaction Wdw (n days)	1		2		3		4		5		10	
Contract	WTI	Brent	WTI	Brent	WTI	Brent	WTI	Brent	WTI	Brent	WTI	Brent
Constant	0.0004	0.0005	0.0004	0.0003	0.0006	0.0004	0.0007	0.0004	0.0007	0.0005	0.0007	0.0005
	(0.2804)	(0.1511)	(0.2117)	(0.2862)	(0.0760)	(0.2157)	(0.0452)	(0.2356)	(0.0503)	(0.1842)	(0.1156)	(0.1668)
R_{t-1}	-0.0003	-0.0127	0.0044	-0.0169	0.0068	-0.0214	0.0018	-0.0204	0.0022	-0.0198	0.0000	-0.0240
	(0.9806)	(0.3728)	(0.7529)	(0.2217)	(0.6171)	(0.1164)	(0.8932)	(0.1331)	(0.8713)	(0.1436)	0.9981	0.0731
BDB_t^n	-0.0021	0.0000	-0.0005	0.0005	-0.0003	0.0020	-0.0004	0.0016	0.0009	0.0015	0.0013	0.0010
	(0.1995)	(0.9861)	(0.6630)	(0.7104)	(0.8066)	(0.0587)	(0.6776)	(0.1199)	(0.3734)	(0.1267)	(0.1448)	(0.2798)
BUB_t^n	-0.0008	-0.0009	**-0.0037**	-0.0010	**-0.0036**	**-0.0037**	**-0.0026**	**-0.0033**	**-0.0028**	**-0.0033**	**-0.0020**	**-0.0016**
	(0.6115)	(0.5528)	**(0.0022)**	(0.4083)	**(0.0007)**	**(0.0005)**	**(0.0091)**	**(0.0010)**	**(0.0034)**	**(0.0006)**	**(0.0256)**	**(0.0815)**
ADB_t^n	-0.0010	0.0004	0.0020	**0.0022**	**0.0025**	**0.0020**	0.0010	**0.0026**	0.0011	**0.0031**	0.0009	0.0014
	(0.5697)	(0.8022)	(0.1056)	**(0.0857)**	**(0.0205)**	**(0.0733)**	(0.3157)	**(0.0136)**	(0.2594)	**(0.0020)**	(0.3064)	(0.1458)
AUB_t^n	-0.0016	**-0.0066**	-0.0014	**-0.0037**	**-0.0028**	**-0.0022**	**-0.0019**	**-0.0023**	**-0.0023**	**-0.0028**	**-0.0017**	**-0.0019**
	(0.3352)	**(0.0001)**	(0.2516)	**(0.0028)**	**(0.0087)**	**(0.0382)**	**(0.0530)**	**(0.0250)**	**(0.0147)**	**(0.0044)**	**(0.0513)**	**(0.0398)**

Table 5: Tests of Conditional Effects (OLS): WTI and Brent

Reaction Wdw (n days)	1	2	3	4	5	10
Constant	-0.0082	-0.0049	0.0014	0.0002	0.0011	0.0086
	(0.3718)	(0.6259)	(0.8976)	(0.9893)	(0.9301)	(0.6055)
R_{t-1}	-0.0645	-0.0469	-0.0562	-0.0561	-0.0545	-0.0670
	(0.0004)	(0.0017)	(0.0001)	(0.0000)	(0.0001)	(0.0000)
BDB_t^n	0.0335	**0.0429**	**0.0424**	**0.0524**	**0.0593**	**0.0881**
	(0.1214)	**(0.0114)**	**(0.0080)**	**(0.0011)**	**(0.0003)**	**(0.0000)**
BUB_t^n	-0.0217	**-0.0577**	**-0.0637**	**-0.0663**	**-0.0729**	**-0.1034**
	(0.3214)	**(0.0007)**	**(0.0001)**	**(0.0000)**	**(0.0000)**	**(0.0000)**
ADB_t^n	0.0165	**0.0591**	**0.0465**	**0.0590**	**0.0853**	**0.0913**
	(0.5124)	**(0.0011)**	**(0.0050)**	**(0.0003)**	**(0.0000)**	**(0.0000)**
AUB_t^n	-0.0007	**-0.0456**	**-0.0452**	**-0.0585**	**-0.0855**	**-0.0951**
	(0.9779)	**(0.0130)**	**(0.0068)**	**(0.0004)**	**(0.0000)**	**(0.0000)**

Table 6: Tests of Conditional Effects (OLS): WTI-Brent Spread

hypotheses to be rejected. More importantly, if all hypothesis tests are mutually independent then the probability of rejecting *at least* one true null hypothesis - a concept commonly referred to as the *familywise error rate* - is given by the very high level of $1-(1-\alpha)^n = 1-0.95^{100} = 0.994$. Indeed, even if the hypothesis tests are not mutually independent then it is still possible to place an upper bound on the familywise error rate, given by $\min(n \times \alpha, 1)$. So in the example of the 100 hypothesis tests here, the familywise error rate is bounded by one.

Several techniques have been developed to control for this problem. The literature has evolved over recent recent decades, and in particular over recent years, towards more generalised procedures that offer the advantage of greater *power* over earlier procedures, where power is loosely defined, as in Romano *et al.* (2010), as the ability to reject a null hypothesis when it is false. Earlier procedures in the literature suffer from excessive conservativeness, in the sense that in attempting to control for false discoveries such procedures make it very difficult to identify *true discoveries* (i.e. rejection of *false* null hypotheses). Recent generalised procedures seek to relax this constraint and so increase the power of the testing. A suite of such techniques will be described next, which will be applied to the empirical analysis presented so far.

4.1 Generalised Familywise Error Rate Techniques

Before introducing the generalised concept, first note that the familywise error rate (FWER) is defined as the probability that at least *one or more* false discoveries occur. Consistent with the notation of Romano *et al.* (2010), the following definition is made:

$$FWER \equiv P\left\{\text{reject at least one null hypothesis } H_{0,i} : i \in I\right\},$$

where $H_{0,i}, i = 1, \ldots, s$, is a set of null hypotheses $(s \geq 1)$ and I is the set of true null hypotheses. So the FWER describes the probability of making at least one false discovery. Controlling the FWER involves setting a significance level α and requiring that $FWER \leq \alpha$.

This approach is particularly conservative and so as a result is criticised for lacking *power*. The greater the total number of hypotheses s, the more difficult it is to make true discoveries.

To deal with these weaknesses, the concept of the generalised FWER has been considered in the literature. The generalised FWER seeks to control for k (where $k \geq 1$) or more false discoveries and, in so doing, allows for greater power in MHT applications. The generalised k-FWER is defined as follows:

$$k\text{-}FWER \equiv P\left\{\text{reject at least } k \text{ null hypothesis } H_{0,i} : i \in I\right\}.$$

Controlling the k-FWER involves setting a significance level α and requiring that k-FWER $\leq \alpha$. The choice of k is set by the user and the greater this choice then the greater the power in identifying true discoveries, at the expense of potentially making more false discoveries along the way. See Romano *et al.* (2010) for a full discussion.

Given the availability of p-values from the hypothesis testing, p-value based MHT procedures are used to control for the multiple comparisons problem. Two classes of procedure will be used; the first class using the k-FWER and the second using the FDP. Two specific procedures from each class will be then used and these are described below. For this, consider the hypotheses $H_{0,(i)}, i = 1, \ldots, s$, ordered from the most significant down to the least significant, i.e. where the p-values are such that $\hat{p}_{(1)} \leq \hat{p}_{(2)} \ldots \leq \hat{p}_{(s)}$.

Generalised Bonferroni (GB). The generalised Bonferroni method is defined by Romano *et al.* (2010) whereby the significance level is adjusted such that hypothesis $H_{0,(i)}, i = 1, \ldots, s$, is deemed rejected if and only if

$$\hat{p}_{(i)} \leq \alpha_{(i)} \equiv k \cdot \alpha / s.$$

This procedure has the advantage of being robust to the dependence structure of the hypothesis tests.

Generalised Holm (GH). Extends the single step nature of the GB methodology to a superior *stepwise* one (Romano *et al.*, 2009). Lehmann and Romano (2005) propose a a generalisation of Holm (1979) with the following set of cut-off values for comparison against the ordered p-values $\hat{p}_{(i)}$:

$$\alpha_{(i)} \equiv \begin{cases} \frac{k\alpha}{s}, & i \leq k \\ \frac{k\alpha}{s+k-i}, & i > k \end{cases}.$$

This procedure is again robust to the dependence structure of the hypothesis tests, with the additional advantage of being stepwise.

4.2 Empirical Results Revisited

In light of the discussion above, we revisit the empirical results reported in Section 3 and apply both the GB and GH methods to control for the multiple comparisons problem. As noted earlier, a total of 369 coefficient hypothesis tests are performed between the various barrier and conditional effects testing. For the GB and GH implementations, we set the generalising parameter $k = \lfloor 369 \times 5\% \rfloor = 18$, such that no more than 5% of the tests represent false discoveries. We control the generalised familywise error rate k-FWER at the three statistical significance levels of $\alpha = 1\%$, 5% and 10%. Under the single step GB method, these significance levels lead to respective adjusted cut-off values of 0.00049, 0.00244 and 0.00488. So, for example, if we control the generalised familywise error rate at the $\alpha = 5\%$ level then we will only consider a result to be statistically significant if the associated p-value is less than 0.00244. The GH method with its stepwise construction aligns exactly with the GB method for the hypothesis test indices 1-18 and then recursively adjusts the cut-off values for all hypothesis test indices beyond 18. The GB and GH in this study lead to the exact same conclusions and so we proceed with describing just the single step GB from here on out.

Returning to the barrier test results in Tables 2 and 3 and the tests of conditional effects in Tables 5 and 6, we re-evaluate the results by applying the three GB cut-off values 0.00049, 0.00244 and 0.00488 that respectively correspond to the 1%, 5% and 10% significance levels for the generalised familywise error rate. Test results significant at these α-levels are highlighted in the tables by the p-values that are underlined. With this MHT procedure, the story that emerges is quite different but is one that is far more robust in its control of the multiple comparison problem and so is one in which we can be far more confident from a statistical perspective. In particular, the evidence for psychological barriers is much reduced in this set up but represents evidence in which we may stand over with much greater confidence. Taking first the barrier proximity tests of Table 2, it can be seen that price clustering appears to only now be a feature for WTI and only for the two barrier ranges BR^2 and BR^3. However in contrast, from Table 3, the positive coefficient values γ that provide evidence of price clustering for both WTI and Brent around the 10s psychological barriers are shown to hold under the MHT framework. Turning to the tests of conditional effects set out in Tables 5 and 6, it can be seen that much of the evidence for psychological barriers effects falls away under the GB procedure. In particular, it can be seen that the previously identified evidence for general support at the $10 barrier levels for both WTI and Brent do not hold. Indeed, it is only for the 5-day reaction window that we see evidence hold for Brent. The evidence for the $10 barrier levels providing general resistance when barrier breaches occurs due to rising prices holds much better under the MHT framework. However, it is notable that this only occurs for Brent and not for WTI. It can be seen that psychological barrier effects emerge for Brent under the GB procedure for the 1-, 2- and 5-day reaction windows. So, under our robust MHT framework, it emerges that there are significant psychological barrier effects for Brent that we do not see with WTI. We argue that this difference between Brent and WTI is linked to the uncertainty in determining fundamental value in the case of Brent, whereas WTI pricing is closely tied to Cushing inventory levels and thus has relatively less ambiguity in determining fundamental value compared to the more complex determinants of Brent pricing. We link this to the recent arguments that WTI is loosing its position, or indeed may have already lost its position, as a dominant global benchmark for crude oil prices; being replaced by Brent. Kao and Wan (2012) apply the Hasbrouck information share model and show that the ability of WTI in reflecting market conditions has deteriorated over recent years. In fact, the authors argue that Brent has surpassed WTI as a global benchmark since the second half of 2004. The authors explicitly cite the rising inventories at Cushing as the reason behind this deterioration. Jin et al. (2012) use a volatility transmission approach to study the responsive of WTI, Brent and Dubai crude oils to market shocks and show that WTI is the actually the least responsive of the three. The reason given by the authors for this is the increasingly US domestic, rather than global, nature of the WTI crude oil market. Our findings align with these conclusions where we have shown with robust statistical confidence that psychological barriers are a feature of the Brent crude oil market and not of the WTI market, hence supporting the notion that Brent has replaced WTI as the key global crude oil benchmark.

Turning to the psychological barrier effects in the WTI-Brent spread, it is notable that the $1 barrier results hold particularly well under the GB implementation, with the general support evidence holding across all reaction windows and the general resistance evidence holding for the 4-, 5- and 10-day reaction windows when the MHT framework is applied. For the results of the two sub-sample periods, similar conclusions emerge. Interestingly, for the post-2006 period, none of the limited test results that were identified as significant under the traditional 1%, 5% and 10% levels hold under the GB procedure. For the pre-2007 period, it can be seen again that in relation to barriers providing general support to oil prices, evidence only holds for Brent over the 5-day reaction window. The evidence for barriers providing general support to oil prices however holds for Brent across all reaction windows considered, with evidence holding even for WTI over the 3-day reaction window. Again, in complete contrast, the evidence for psychological barrier effects in the WTI-Brent spread holds much better under the GB implementation, with evidence for general support and general resistance holding across all reaction windows baring the short 1-day window.

5 Conclusion

This paper significantly extends the prior testing of psychological barriers in crude oil markets through a number of theoretical and testing advances that offer novel perspectives on how these psychological barriers are likely to influence oil futures pricing. Focusing on $10 barrier regions (movements through a price ending in a 0 dollar digit) we show that there is heightened media coverage of these price points providing a practical justification for increased trader attention to such barriers. We show that psychological barriers only appear to influence pricing in the pre-credit crisis period of 1990-2007 and that such psychological barrier effects dissipated during the boom and bust in oil prices over the later years of the last decade. Significant focus is also placed on determining the speed of market reaction to barrier breaches and we find significant market reaction up to 5 trade days (and in some case up to 10 trade days) subsequent to breaching psychological barriers. In line with our hypothesis that the greater uncertainty around Brent fundamental value leads to a greater role for psychological barriers in pricing for these contracts, we provide evidence that there are significant psychological barrier effects for Brent that we do not see with WTI. We argue that this difference between Brent and WTI is linked to the uncertainty in determining fundamental value in the case of Brent, whereas WTI pricing is closely tied to Cushing inventory levels and thus has relatively less ambiguity in determining fundamental value compared to the more complex determinants of Brent pricing. We further link this to the recent arguments that Brent has overtaken WTI as a dominant global benchmark for crude oil prices. This conclusion emerges from our application of generalised multiple hypothesis testing approaches to our extensive suite of testing. We recognise that such multiple hypothesis testing introduces the multiple comparisons problem whereby statistically significant results may be identified by pure chance alone. We apply two generalised techniques to control for the likelihood of making false discoveries and so we can be robustly confident that psychological barriers are a feature of the Brent crude oil market and not of the WTI market. Further research could fruitfully investigate similar psychological barrier effects in other professionally traded energy and commodity markets. The multiple hypothesis testing framework offers statistical rigour to this future work, while more generally it provides an impetus to explicitly account for the multiple comparisons problem in empirical-based energy and commodity market studies.

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A Tests of Conditional Effects: Subsamples

Reaction Wdw (n days)	1		2		3		4		5		10	
Contract	WTI	Brent	WTI	Brent	WTI	Brent	WTI	Brent	WTI	Brent	WTI	Brent
Constant	0.0002	0.0003	0.0003	0.0002	0.0004	0.0003	0.0004	0.0002	0.0005	0.0003	0.0002	0.0003
	(0.5118)	(0.3568)	(0.4273)	(0.5482)	(0.2782)	(0.4413)	(0.2660)	(0.5198)	(0.2388)	(0.3805)	(0.6315)	(0.4275)
R_{t-1}	0.0223	-0.0014	0.0258	-0.0037	0.0306	-0.0048	0.0234	-0.0058	0.0250	-0.0010	0.0221	-0.0093
	(0.1724)	(0.9327)	(0.1080)	(0.8146)	(0.0537)	(0.7612)	(0.1358)	(0.7104)	(0.1115)	(0.9497)	(0.1553)	(0.5500)
BDB_t^n	**-0.0041**	**0.0039**	-0.0003	**0.0029**	0.0006	**0.0046**	0.0009	**0.0045**	0.0015	**0.0047**	**0.0030**	**0.0033**
	(0.0604)	**(0.0807)**	(0.8602)	**(0.0813)**	(0.6845)	**(0.0018)**	(0.4775)	**(0.0014)**	(0.2339)	**(0.0007)**	**(0.0087)**	**(0.0114)**
BUB_t^n	0.0003	0.0015	**-0.0041**	0.0007	**-0.0034**	**-0.0042**	**-0.0025**	**-0.0037**	**-0.0027**	**-0.0050**	**-0.0024**	**-0.0026**
	(0.8919)	(0.4806)	**(0.0102)**	(0.6684)	**(0.0139)**	**(0.0044)**	**(0.0582)**	**(0.0074)**	**(0.0314)**	**(0.0002)**	**(0.0364)**	**(0.0404)**
ADB_t^n	-0.0005	-0.0030	0.0024	0.0012	**0.0033**	**0.0030**	0.0008	**0.0032**	0.0015	**0.0059**	0.0018	**0.0031**
	(0.8279)	(0.1832)	(0.1515)	(0.5000)	**(0.0215)**	**(0.0478)**	(0.5632)	**(0.0238)**	(0.2373)	**(0.0000)**	(0.1305)	**(0.0191)**
AUB_t^n	-0.0009	**-0.0111**	-0.0015	**-0.0069**	**-0.0042**	**-0.0056**	**-0.0024**	**-0.0052**	**-0.0031**	**-0.0073**	**-0.0026**	**-0.0046**
	(0.6939)	**(0.0000)**	(0.3678)	**(0.0000)**	**(0.0030)**	**(0.0001)**	**(0.0750)**	**(0.0002)**	**(0.0127)**	**(0.0000)**	**(0.0204)**	**(0.0003)**

Table 7: Tests of Conditional Effects (OLS): Pre-2007

Reaction Wdw (n days)	1		2		3		4		5		10	
Contract	WTI	Brent	WTI	Brent	WTI	Brent	WTI	Brent	WTI	Brent	WTI	Brent
Constant	0.0008	0.0009	0.0010	0.0008	0.0016	0.0010	0.0021	0.0011	0.0020	0.0010	0.0032	0.0019
	(0.3000)	(0.1858)	(0.2316)	(0.2416)	(0.0777)	(0.2120)	(0.0252)	(0.1603)	(0.0393)	(0.2344)	(0.0087)	(0.0841)
R_{t-1}	-0.0531	-0.0464	-0.0458	-0.0571	-0.0477	-0.0720	-0.0477	-0.0666	-0.0494	-0.0717	-0.0534	-0.0684
	(0.0725)	(0.1121)	(0.1010)	(0.0381)	(0.0786)	(0.0079)	(0.0743)	(0.0139)	(0.0626)	(0.0072)	(0.0407)	(0.0094)
BDB_t^n	-0.0004	**-0.0043**	-0.0013	-0.0024	-0.0017	-0.0009	-0.0025	-0.0017	-0.0004	-0.0015	-0.0016	-0.0013
	(0.8713)	**(0.0804)**	(0.5193)	(0.2044)	(0.3171)	(0.5866)	(0.1230)	(0.2709)	(0.8248)	(0.3189)	(0.3120)	(0.3551)
BUB_t^n	-0.0023	-0.0038	**-0.0034**	**-0.0031**	**-0.0041**	**-0.0037**	**-0.0034**	**-0.0033**	**-0.0036**	**-0.0023**	**-0.0029**	-0.0019
	(0.3765)	(0.1102)	**(0.0800)**	**(0.0892)**	**(0.0177)**	**(0.0212)**	**(0.0339)**	**(0.0262)**	**(0.0221)**	**(0.1123)**	**(0.0695)**	(0.1839)
ADB_t^n	-0.0023	0.0038	0.0011	0.0030	0.0013	0.0007	0.0011	0.0016	0.0006	0.0004	0.0003	0.0002
	(0.4089)	(0.1550)	(0.6025)	(0.1248)	(0.4622)	(0.6791)	(0.5173)	(0.3035)	(0.7064)	(0.7759)	(0.8733)	(0.8816)
AUB_t^n	-0.0017	-0.0019	-0.0011	-0.0002	-0.0014	0.0015	-0.0017	0.0008	-0.0017	0.0015	-0.0012	0.0001
	(0.5473)	(0.4473)	(0.5904)	(0.9298)	(0.4433)	(0.3682)	(0.3095)	0.6166	0.2731	0.3086	0.4524	0.9528

Table 8: Tests of Conditional Effects (OLS): Post-2006

Reaction Wdw (n days)	1	2	3	4	5	10
Constant	-0.0072	-0.0032	-0.0023	-0.0041	-0.0015	0.0076
	(0.2796)	(0.6549)	(0.7711)	(0.6188)	(0.8620)	(0.5070)
R_{t-1}	-0.1074	-0.0806	-0.0935	-0.0942	-0.0961	-0.1123
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
BDB_t^n	**0.0580**	**0.0705**	**0.0699**	**0.0737**	**0.0829**	**0.0951**
	(0.0023)	**(0.0000)**	**(0.0000)**	**(0.0000)**	**(0.0000)**	**(0.0000)**
BUB_t^n	**-0.0574**	**-0.0701**	**-0.0707**	**-0.0628**	**-0.0821**	**-0.1084**
	(0.0024)	**(0.0000)**	**(0.0000)**	**(0.0000)**	**(0.0000)**	**(0.0000)**
ADB_t^n	**0.0494**	**0.0732**	**0.0622**	**0.0715**	**0.0868**	**0.0841**
	(0.0225)	**(0.0000)**	**(0.0000)**	**(0.0000)**	**(0.0000)**	**(0.0000)**
AUB_t^n	0.0245	**-0.0564**	**-0.0534**	**-0.0704**	**-0.0839**	**-0.0829**
	(0.2593)	**(0.0003)**	**(0.0001)**	**(0.0000)**	**(0.0000)**	**(0.0000)**

Table 9: Tests of Conditional Effects (OLS): WTI-Brent Spread Pre-2007

Reaction Wdw (n days)	1	2	3	4	5	10
Constant	-0.0175	-0.0238	0.0116	0.0113	0.0016	0.0095
	(0.6266)	(0.5863)	(0.8198)	(0.8474)	(0.9806)	(0.9324)
R_{t-1}	-0.0531	-0.0359	-0.0419	-0.0423	-0.0352	-0.0453
	(0.1813)	(0.2336)	(0.1368)	(0.1208)	(0.1891)	(0.0813)
BDB_t^n	0.0239	0.0176	0.0032	0.0130	0.0109	0.0496
	(0.6668)	(0.7023)	(0.9443)	(0.7908)	(0.8396)	(0.5683)
BUB_t^n	0.0426	-0.0342	-0.0555	**-0.0818**	-0.0524	-0.0718
	(0.4586)	(0.4658)	(0.2241)	**(0.0860)**	(0.3095)	(0.4036)
ADB_t^n	-0.0410	0.0460	0.0246	0.0464	0.0900	0.1060
	(0.5393)	(0.3525)	(0.6080)	(0.3569)	(0.1002)	(0.2231)
AUB_t^n	-0.0195	-0.0162	-0.0275	-0.0245	-0.0779	-0.1131
	(0.7818)	(0.7465)	(0.5610)	(0.6166)	(0.1389)	(0.1880)

Table 10: Tests of Conditional Effects (OLS): WTI-Brent Spread Post-2006