IIIS Discussion Paper

No.459/November 2014

Behavioral Influences in Non-Ferrous Metals Prices

Mark Cummins, Michael Dowling, Brian M. Lucey

IIIS Discussion Paper No. 459

Behavioral Influences in Non-Ferrous Metals Prices

Mark Cummins, Michael Dowling, Brian M. Lucey

Behavioral Influences in Non-Ferrous Metals Prices

Mark Cummins, Michael Dowling, Brian M. Lucey

Abstract

Recent research has identified the presence of behavioral influences on traders in predominantly professionally traded markets such as oil, gold, and foreign exchange. Previous research had largely confined behavioral-based investigations to equity markets due to an assumption that noise traders would drive any influence and these traders were mainly absent from the professionally traded markets. This paper extends this research to the non-ferrous metals markets and demonstrates similar influences on prices. It is shown that psychological price barriers, where there is predictable trading patterns around psychologically important price points, are important. Specifically, lead, zinc, and aluminium alloy, show anomalous price reactions in the days particularly following a breach of a $1,000 price point. There is also evidence presented of negative price clustering before key price barriers. Subperiod tests further indicate that the relevant psychological price point is dependent on average prices. Recognising the multiple hypothesis testing nature of the study, generalized Bonferroni corrections are implemented to provide a robust control for the possibility of data mining. This represents a first investigation of behavioral influences in non-ferrous metals prices, and suggests these markets are not immune to trader biases influencing the setting of prices.

JEL Classification: G13, G14, L61

Keywords: psychological barriers; clustering; non-ferrous metals.

Mark Cummins (corresponding author): DCU Business School, Dublin City University, Glasnevin, Dublin 9, Ireland. Email: Mark.Cummins@dcu.ie. Michael Dowling: DCU Business School, Dublin City University, Glasnevin, Dublin 9, Ireland. Email: Michael.Dowling@dcu.ie. Brian M. Lucey: School of Business, Trinity College Dublin, Dublin 2, Ireland; and Faculty of Economics, University of Ljubljana, Ljubljana, Slovenia. Email: blucey@tcd.ie.

1 Introduction

> Copper looks set to test the \$10,000 a ton mark again, supported by strong import figures from China
>
> Commerzbank, 13th April 2011

> Aluminum futures have settled below the symbolic \$2,000-per-tonne mark on the London Metal Exchange for a full week of trading, suggesting that weak fundamentals might finally be catching up with the speculation-driven market.
>
> Metal Bulletin, 25th August 2009

The idea that certain price points in the non-ferrous metals markets (and indeed most financial markets) are symbolic or psychologically important is taken as a given in media coverage and market analysis. Yet this behavioral aspect of prices for these markets has never been investigated. In fact, no behavioral analysis has previously been applied to develop a deeper understanding of how non-ferrous metals are priced. This is despite behavioral finance principles having been successfully applied in a number of other professionally-traded markets, such as oil, gold, and foreign exchange, and showing a strong ability to improve knowledge of trader decision-making and price setting in these markets.

Researchers in equity pricing have repeatedly shown that some price points are more psychologically important than others to market participants and that this influences prices (e.g. Donaldson and Kim, 1993). To illustrate this research: the Dow Jones Industrial Average breaking through 10,000 points is argued to be a more prominent and salient event than the price reaching 9,500. Apple's share price approaching \$1,000 is considered to be more noteworthy to investors than the shares approaching \$1,050. Aggregating market price events like these, equity researchers have shown that for psychologically important price points, prices tend to show abnormal clustering (often interpreted as a reluctance of prices to cross through a price point), and also that pricing in the days immediately following a breach of a price barrier tends to be predictable. These findings in equity markets were initially attributed to the actions of poorly informed small traders, but recent research has extended the area to markets that are predominantly professionally traded. Thus, Mitchell and Izan (2006) find psychological barriers to be evident in foreign exchange markets; Aggarwal and Lucey (2007) find clustering and barriers in gold prices; and most recently Dowling, Cummins, and Lucey (2014) show these effects in oil futures prices. For example, in oil futures it is found that whole $10 price points are psychologically important in these markets, with prices showing retrenchment subsequent to breaching a $10 barrier through rising prices.

We extend this research to the non-ferrous metals markets. The testing approach is adapted from Dowling et al. (2014) and Aggarwal and Lucey (2007) and focuses on detecting the presence of price clustering and psychological barriers in the prices of non-ferrous metals traded on the London Metal Exchange (LME). The seven non-ferrous metals selected are: aluminium, aluminium alloy, copper, lead, nickel, tin, and zinc; and consist of daily cash contract prices from 03 December 1993 to 05 December 2013. Key findings include that price clustering is present for the majority of metals around whole $1,000 price points. The most common form of clustering is negative clustering, where there is a lower frequency of prices in psychologically important price regions. Further there is evidence of directional price movements for a number of metals in the days immediately after prices pass through a $1,000 barrier level. Subperiod tests indicate that these findings are still a feature in today's markets, but that a $100 price barrier was the most relevant in the early period when metals traded at significantly lower average prices compared to the most recent period.

Given the amount of tests undertaken in the study there is a risk of spurious findings (a common criticism of behavioral finance studies; see e.g. Sullivan, Timmermann, and White, 2001; and more recently for general finance research by Harvey, Liu, and Zhu, 2014). With 1,134 coefficients tested across the study, some coefficients would, by chance alone, appear to be significant even if all null hypotheses were true. We control for this possibility through implementing a Generalized Bonferroni correction (Romano, Shaikh, and Wolf, 2010); the practical implication of which is that only coefficients with a p-value less than 0.00503 are considered to be significant. This adds a strong element of reassurance as to the robustness of the findings.

The implications of these findings relate, firstly, to the efficiency of the markets. A price passing through a \$100 or a \$1,000 level should not cause predictability of subsequent price movements, nor should prices cluster around price levels. Yet, we show this effect in these markets. This suggests that (at least for this particular price feature) a number of the non-ferrous metals markets are not even weak-form efficient. There is, secondly, a trading implication. For example, one of the most notable findings is that aluminium alloy prices retrench by 1.2 percent in the day immediately after rising through a \$1,000 barrier. Other metals also show significant predictability of price movements after passing through a psychological price level. The final benefit of the study is of a more general nature; the demonstration that the behavioral biases shown to be present in equity markets, and more recently in other professionally-traded markets such as oil, gold, and foreign exchange, are also a feature of the non-ferrous metals markets. This provides a justification for further investigation of behavioral biases in these markets.

The remainder of the paper is structured as follows. In Section 2 the prior research on non-ferrous metals pricing is reviewed. Section 3 provides an overview of the price clustering and psychological barriers literature and relates this to the non-ferrous metals markets. The data and methodology is discussed in Section 4, while the empirical findings are presented and analyzed in Section 5. Section 6 concludes and provides some potential direction for further research.

2 Non-Ferrous Metals Prices

Watkins and McAleer (2004) provide a comprehensive meta-analysis of research on non-ferrous metals prices published between 1980 and 2002. One of the striking notes from their analysis is how limited the study of non-ferrous metals prices is, with just 45 papers identified over the entire period. Key topics for the extant research focused on market efficiency, risk premia, and volatility, with explanatory models generally using either macroeconomic, industrial, or financial variables to understand price dynamics. The London Metals Exchange (LME) is the primary data source utilized in prior research and studies are commonly restricted to the seven main industrially-used non-ferrous metals (the 'base metals'), namely; aluminium, aluminium alloy, copper, lead, nickel, tin, and zinc. While silver is sometimes included, it is primarily classified as a precious metals despite also having significant industrial uses. Copper is the most widely studied, being generally regarded as the most competitive market due to low industry concentration of suppliers and consumers.

Todorova, Worthington, and Souček (2014) analyze volatility spillovers between aluminium, copper, lead, zinc, and nickel LME futures for 2006 to 2012 and find strong evidence of such spillovers, especially post the financial crisis period, thus providing a rationale for analyzing the metals together. One explanation offered for these spillover effects is the industrial interrelationships between the metals, for example between aluminium and nickel for the automobile industry, and copper and lead for the electronics and electrical sector.

Long-term pricing studies of metals also show an increased interrelationship between metals prices and other financial markets over time. Cochran et al (2012) find stronger evidence of a relationship between copper and equity market volatility post the 2008 financial crisis. Buncic and Moretto (2014) provide comprehensive additional support for this increased inter-relationship between copper and equity market volatility, and attribute this, in part, to a general increase in financialization across all financial markets. The financialization hypothesis, where the increased presence of financial market actors (as opposed to industrial actors) leads to increased speculation in markets, has also been noted in other professionally traded markets such as oil (e.g. Tokic, 2011). One example of this in non-ferrous metals is their increased use as collateral in the Chinese shadow banking sector (Tang and Zhu, 2014).

Despite the preponderance of studies applying theories based on investor psychology to understanding equity market pricing (e.g. see the comprehensive reviews contained in Hirshleifer, 2001; 2014), there is no investigation of this area in metals markets. The aforementioned Watkins and McAleer (2004) meta-analysis could find no behavioral-based investigations of metals prices. A longstanding argument against the application of investor psychology in professionally traded markets is due to the absence of small investors who are presumed to drive noise trading in equity markets . However studies have increasingly noted that professional traders can also be affected by similar behavioral biases. For example, Coval and Shumway (2005) finds Chicago Board of Trade traders to be influenced by loss aversion in their trading, while O'Connell and Teo (2009) find professional currency traders to be affected by overconfidence.

Pierdzioch, Rülke, and Stadtmann (2013) do find that market analysts for a number of the non-ferrous metals show the same behaviorally-driven forecasting errors as seen in other financial markets, but no study of the impact on market prices is attempted. No other study could be located that investigates a psychology-based explanation for trading in these markets. The closest research in the area is Coakley, Dollery, and Kellard (2011) who find evidence of long-term memory in copper pricing, which they argue could be consistent with noise trader risk being priced in copper, although they do not elaborate on this. Also, an attempt by Heaney (2006) to explain copper, lead and zinc prices through either inventory levels or a convenience yield, finds that while these rational approaches are useful "there is still some way to go in fully explaining commodity prices" (p. 392). Thus, there is a significant unknown element to price dynamics in the non-ferrous metals markets, which when combined with the evidence of psychological influences on traders in other professionally traded markets, suggests that behavioral theories of trading might contribute to improved understanding of how base metals markets are priced.

3 Clustering and Psychological Barriers

If markets are efficient then, all things being equal and abstracting from trends and drift, prices should evolve in a manner where the likelihood of any given change is approximately equal. This would in turn result in there being no systemic clusters of prices or psychological price barriers. Price clustering derives from the early work of Osborne (1962) and Niederhoffer (1965) and has since evolved to two distinct threads; clustering *per se*, and the existence of psychological price barriers. Price clustering is the phenomenon of prices showing an excessive frequency of certain digits, while psychological barriers research is concerned with price behavior around certain price points (Mitchell, 2001). The latter area is generally perceived as more important for markets due to its trading implications.

Price clustering has been widely found across financial markets. In equity markets, prices have been shown to cluster around psychologically prominent ending digits (5 and 0) even after controlling for market microstructure issues (Ikenberry and Weston, 2008), while Bhattacharya, Holden, and Jacobsen (2012) relate this equity price clustering to trader behavior. Bharati, Crain and Kaminski (2012), and Narayan, Narayan, and Popp (2011) find price clustering in oil futures, with Bharati et al. (2012) connecting the clustering to trader reaction to the potential for market intervention by oil producers. Aggarwal and Lucey (2007) find clustering to be related to whole \$100 levels for gold prices.

Most research on psychological barriers has concentrated on equity markets (e.g. Donaldson and Kim, 1993; Sonnemans, 2006; Dorfleitner and Klein, 2009), however the existence of these barriers has also been detected in a number of markets primarily traded by professional traders, including foreign exchange (Mitchell and Izan, 2006), gold (Aggarwal and Lucey, 2007), and oil (Dowling et al, 2014). For example, Dowling et al. (2014) argue that whole \$10 price points are psychologically important in oil futures markets and show anomalous trading behaviour around these prices, with Brent futures showing price retrenchment subsequent to breaching a \$10 barrier through rising prices.

One interesting feature of this literature, not previously elaborated upon in prior research, is that for some markets there is clustering around certain digits and evidence of psychological barrier price levels, while for other markets clustering is perhaps better described as anti-clustering, with prices around key levels and certain digits showing a lower frequency. Thus, Dowling et al. (2014) find greater frequency of prices around psychologically important oil price levels, while Aggarwal and Lucey (2007) find lower frequency for gold prices. Donaldson and Kim (1993) find lower frequency around psychologically important Dow Jones Industrial Average price points, while Mitchell and Izan (2006) find some elevated frequency around psychological barrier levels in foreign exchange markets. One distinction that can be drawn between the oil and foreign exchange markets compared to the gold and equities markets is that there is greater potential for intervention by powerful players in the oil and foreign exchange markets (e.g. by OPEC producers in the oil market and national governments in currency markets). This is less of a likelihood in the equity and gold markets. Thus, there might be differential effects in markets dependent on the particular characteristics of that market. In supporting related-market research, Batten, Ciner, and Lucey (2010) note the individual macroeconomic drivers of gold, silver, platinum, and palladium pricing, in their analysis of precious metals markets, despite these markets commonly being grouped together. This is something which we observe in our subsequent metals markets investigations.

4 Data and Methodology

The testing approach is adapted from Dowling et al. (2014) and Aggarwal and Lucey (2007) and focuses on the presence of price clustering and psychological barriers in the prices of non-ferrous metals traded on the London Metal Exchange (LME). The seven non-ferrous metals selected match those of Watkins and McAleer (2006); aluminium, aluminium alloy, copper, lead, nickel, tin, and zinc; and consist of daily cash contract prices from 03 December 1993 to 05 December 2013. Table 1 provides descriptive statistics for the seven metal price series and prices over time are charted in Figure 1. In general the series show a low price variability from 1993 to 2003, followed by a strong price build-up peaking around 2007 driven by emerging markets demand, and a subsequent fall back in prices (although there are differences in price trends across the metals). To differentiate between these two market periods we further test our sample over two subperiods: (i) an early period of December 1993 to November 2003, and (ii) a more recent period of December 2003 to December 2013.

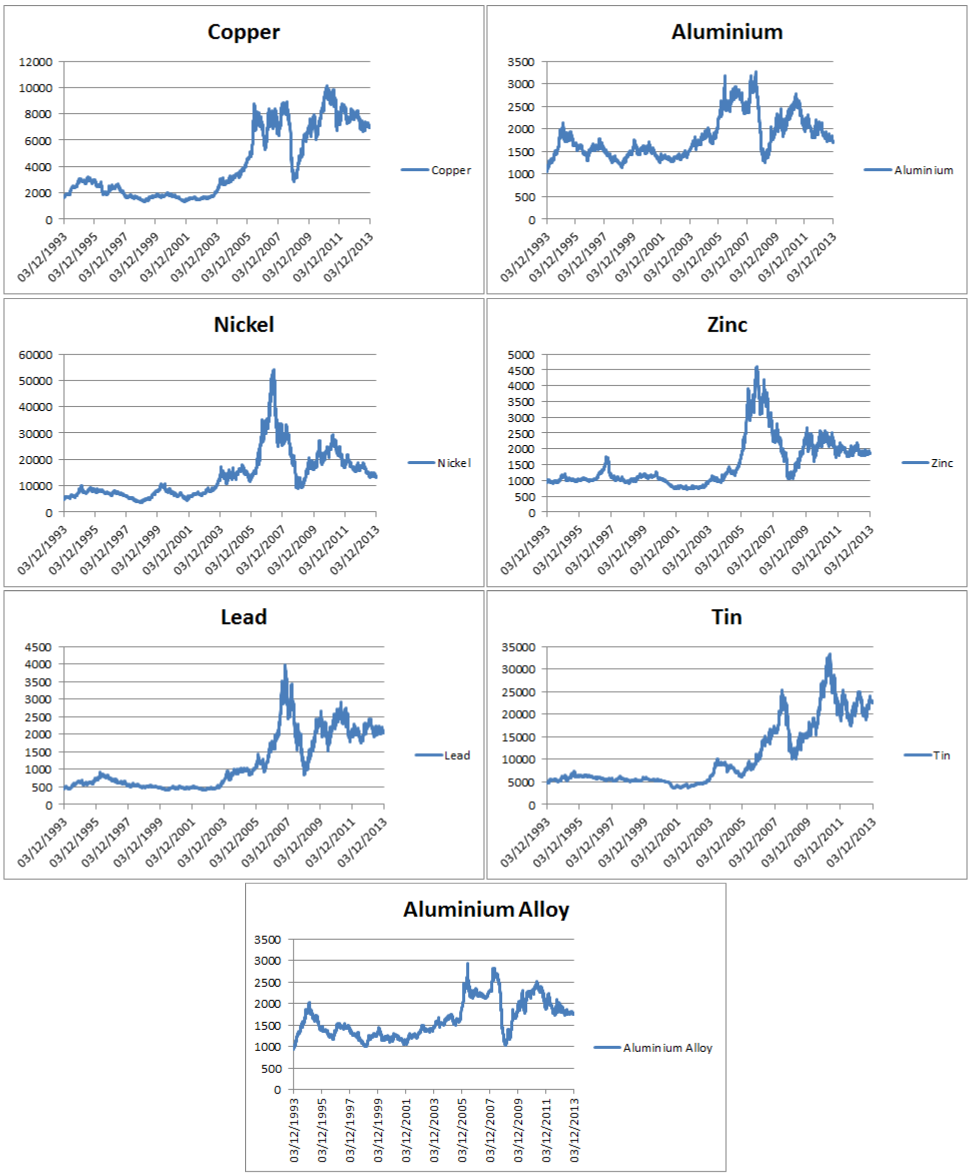


Figure 1: Metals Time Series

Sample Period: 03 Dec 1993 - 05 Dec 2013							
	Copper	Alum	Nickel	Zinc	Lead	Tin	Alum Alloy
Mean	4166.59	1816.13	13608.53	1532.94	1180.54	10613.39	1637.50
Std Dev	2668.42	461.62	8840.92	768.09	798.97	7123.47	427.87
Skew	0.60	0.87	1.54	1.46	0.91	1.08	0.62
Kurt	1.72	2.84	5.78	4.84	2.68	2.91	2.33
Max	10179.50	3271.25	54050.00	4603.00	3989.00	33265.00	2940.00
Min	1318.25	1057.20	3730.50	722.75	400.75	3601.00	925.00

Table 1: Data Descriptive Statistics

Price clustering analysis consists of barrier proximity and barrier kurtosis tests. Barrier proximity tests are designed to measure whether or not price observations on, or near, barriers occur significantly more frequently than a uniform distribution would predict. In general, these tests examine the shape of the frequency distribution for various price digit combinations. The tests of this paper examine the presence of \$100 and \$1,000 psychological barriers. \$100 barrier tests examine the two digits to the immediate left of the decimal point (i.e. -,-XX.-), and the \$1,000 barrier tests examine the two digits to the left of the digit to the immediate left of the decimal point (i.e. -,XX-.-). Specifically three different barrier region ranges are tested: barrier level ± 2, barrier level ± 5, and barrier level ± 10; corresponding, for the \$100 barrier level, to \$98-\$102, \$95-\$105, and \$90-\$110, and the equivalent range for the \$1,000 barrier level. Given the literature noted in Section 3 on differences between markets as to whether there is higher or lower frequency within a barrier region, no firm hypothesis is formed as to whether high or low barrier region frequency will emerge from this clustering analysis, although there is a partial expectation that there will be predominantly negative clustering due to the prior gold market findings of Aggarwal and Lucey (2007). Thus, for the \$100 barrier region there is an expectation of lower frequency of price digits ending in numbers close to \$100.

The barrier proximity tests examine whether there is abnormal frequency in digits around the barrier level, while barrier kurtosis tests go a step further and also allow for a detection of significant abnormal frequency distributions in the barrier region. Barrier kurtosis tests are considered a more robust investigation of the presence of price clustering (Mitchell, 2001). To formally elaborate on the testing; M is defined to be the full range of digits $\{0, \ldots, 99\}$. 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 centered on 00. A price within the defined barrier range is represented by a dummy variable, D^i,$i = BR^1, BR^2, BR^3$, 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. Thus the barrier proximity tests are a test of significance of the dummy variable coefficient. The null hypothesis is that β will be zero, whereas the presence of psychological barriers will result in either lower or higher frequency of M-values at the barrier; for negative clustering β will be negative and significant, with the opposite for positive clustering.

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 frequency of the M-digits being regressed on both their values and the square of their values. The null of no abnormal frequency distribution in the barrier region is determined by the coefficient of γ being zero, while clustering will be shown by a significant positive coefficient and anti-clustering (below expected frequency of M-digits in the barrier range) will be represented by a significant negative coefficient.

The price clustering analysis provides an initial investigation of the presence of behavioral influences on metals prices, but lacks a trading implication. Following the clustering analysis, trading around psychological barriers is tested in order to determine if there is a differential reaction to barriers dependent on the conditions related to the psychological barrier. First, barriers are differentiated based on whether they are approached through rising or falling prices (from above or below), and, conditional on this, price direction following a barrier being breached from above or below is analyzed. The main tests are OLS regressions 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 the following four dummy variables:

- BDB^n, which assigns 1 to the n days *before* a downward breach, i.e. the period before a barrier breach from above due to *downward* or falling prices;
- ADB^n, which assigns 1 to the n days *after* a downward breach, i.e.the period following 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. the period before 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. the period after 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:

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

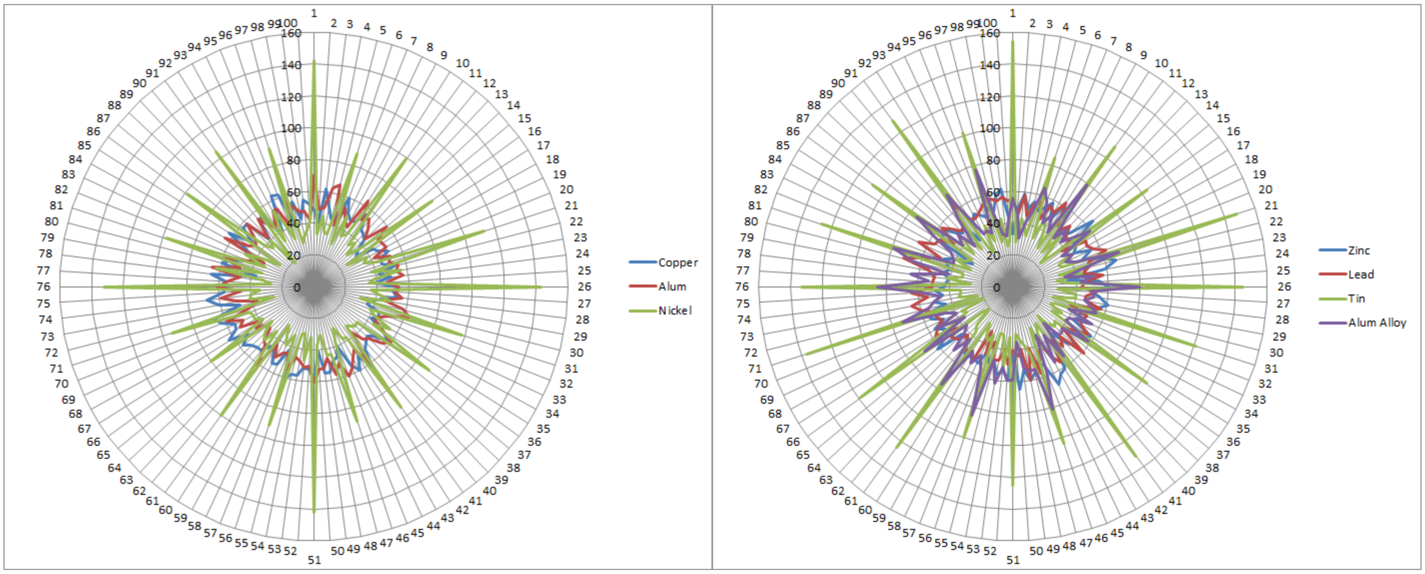
To test the speed of market reaction to barrier breaches, a range of reaction windows of size n days are tested. Specifically, reaction windows of $n = 1, 2, 3, 4, 5$ and 10 days are used, which allows an assessment of the speed of market reaction over and up to the week before and the week after a barrier 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 level, the reaction windows we consider allow us to implicitly take account of false barrier breaches as we look to ascertain if patterns in price behaviour exist subsequent to barrier breaches. Of particular trading interest are the ADB^n and AUB^n dummy variables, as these allow a determination of whether breaching a barrier is followed by continued directional momentum or price retrenchment.

A robustness check is also carried out to control for the multiple hypothesis testing nature of the investigation. The clustering and conditional effect tests outlined above involve a total of 1,134 separate coefficient tests. This leads to a potential multiple comparisons problem where there is a possibility of identifying what appear to be statistically significant coefficients by chance alone, due to so many tests being performed simultaneously. This possibility, akin to data mining albeit inadvertent, is frequently ignored in this area of research and has been a common criticism of behavioral finance research (e.g. Fama, 1998; Sullivan et al., 2001), and has recently been raised as a criticism of most asset pricing models (Harvey et al., 2014). Romano et al. (2010) provide a comprehensive exposition of the issue. A number of *generalised* techniques have been suggested to minimize the generalised familywise error rate, i.e. the probability of making $k \geq 1$ false discoveries from a family of s simultaneous hypothesis tests (Romano et al. (2010) and this study opts for the stepwise generalized Bonferroni procedure (for previous applications of this procedure see Cummins, 2013; Dowling et al., 2014). In this approach the significance level is adjusted such that a hypothesis $H_{0,i}, i = 1, \ldots, s$, is deemed rejected if and only if the associated p-value $p_{(i)} \leq \alpha_{(i)} \equiv k \cdot \alpha / s$, where s is the total number of tests (in this study's case there are 1134 tests across all the barrier proximity, kurtosis, and conditional effects tests), k is the number of false discoveries that is sought to be controlled for, and α is the significance level. In this set up, the generalised Bonferroni ensures that the $P\,(k$ or more false discoveries$) \leq \alpha$. Following Dowling et al. (2014), k is set at 5 percent of the total number of tests, rounded up, (i.e. $k = 57 \approxeq 5\% \times 1134$), and a significance level of $\alpha = 10\%$ is applied to this. This leads to a generalised Bonferroni corrected cut-off value of 0.00503. In the reported findings in the next section any coefficients that are significant under traditional 1%, 5%, and 10% levels are bolded in the tables, while any coefficients where the p-value is lower than the generalised Bonferroni corrected cut-off value of 0.00503 are additionally underlined. The main attention is placed on the latter coefficients due to their enhanced control for the possibility of chance findings.

5 Empirical Results

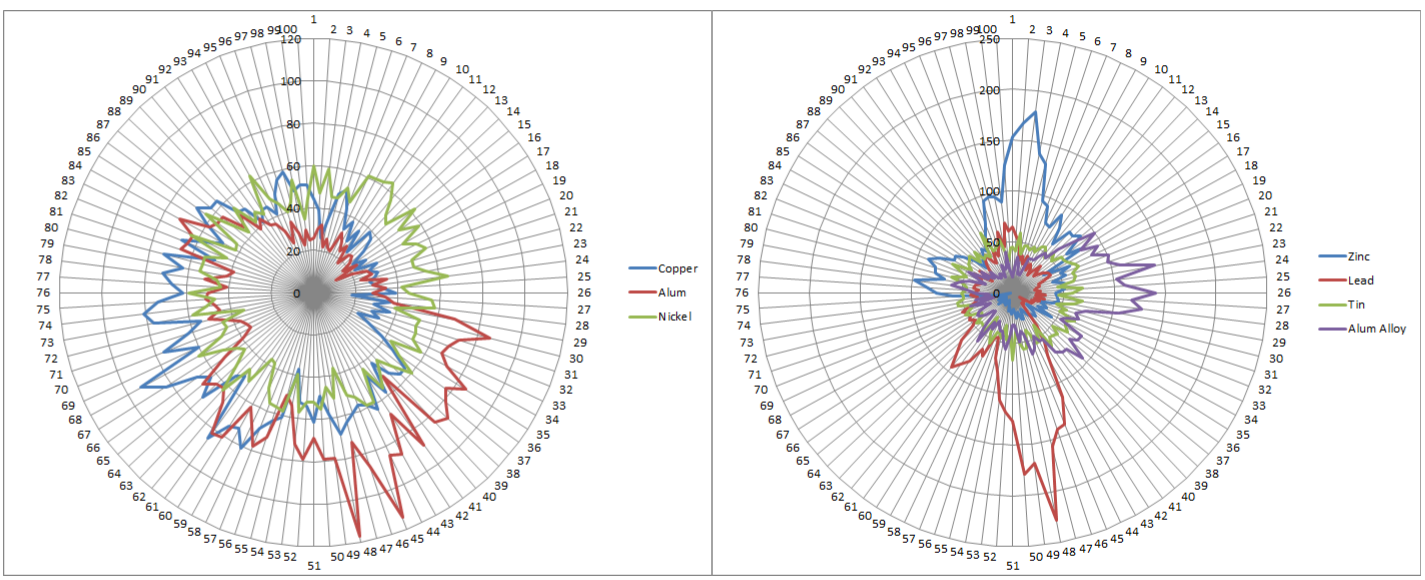
Figures 2-3 present radar charts of the digit frequency distributions for the various metals based on the appropriate digit positions corresponding to the \$100 and \$1000 barrier tests as discussed in the previous section. It is quite clear from the plots that the frequency distributions do not conform to the uniform distribution. So informally it would appear that price clustering may be a feature. The findings from the formal price clustering tests; barrier proximity and barrier kurtosis tests, are contained in Tables 2 and 3. Examining the barrier proximity tests first, there is some evidence of clustering based on these tests. There appears to be very little clustering around \$100 barriers, with only lead showing significant clustering in the $BR^3 \equiv \{90, \ldots, 00, \ldots, 10\}$barrier range. The lack of findings for \$100 barriers suggests this is not an important barrier level, a perhaps unsurprising finding particularly for copper, nickel, tin, given the price ranges these metals traded at over the time period (e.g. copper trades between \$1,318.25 and \$10,179.50; nickel \$3,730.50 to \$54,050.00; tin \$3,601.00 to \$33,265.00). For metals with these price ranges it is difficult to see how crossing a \$100 barrier level would mark a significant market or psychological barrier event. Aluminium, zinc, lead, and aluminium alloy do trade within a narrower range and thus crossing a \$100 barrier might possibly be considered an important psychological barrier event for these metals, however, as mentioned, only lead shows evidence of clustering at this price level.

The evidence for clustering in the \$1,000 barrier level is much stronger. Zinc shows strong positive clustering in all three specifications of the barrier region around \$1,000. For example, zinc has a coefficient of 97.126 for $BR^1 \equiv \{98, 99, 00, 01, 02\}$which can be interpreted as showing that the frequency of prices occurring between \$980 and \$1,020 is higher by 97 observations than the expected frequency level. Copper, aluminium, tin, and aluminium alloy, also show significant evidence of abnormal price frequency in the barrier levels, however these series show negative-clustering in contrast to zinc. This means there is a significantly lower frequency of prices in the barrier regions compared to other price ranges and compared to the frequency expectation. Of these findings, aluminium, zinc, and aluminium alloy are robust to the generalized Bonferroni correction. Overall these findings



-,-XX.– represents the two digits to the immediate left of the decimal point, as required for the $100 barrier tests.

Figure 2: Radar Charts of Digit Frequency Distributions: Digit Positions -,-XX.–



-,XX-.– represents the two digits to the left of the digit to the immediate left of the decimal point, as required for the $1,000 barrier tests.

Figure 3: Radar Charts of Digit Frequency Distributions: Digit Positions -,XX-.–

	BR^1		BR^2		BR^3	
	β	(p-value)	β	(p-value)	β	(p-value)
			\$100 Barriers			
Copper	0.705	(0.844)	-1.944	(0.435)	-0.020	(0.992)
Alum	1.126	(0.734)	2.755	(0.232)	1.125	(0.526)
Nickel	9.337	(0.484)	4.900	(0.599)	3.717	(0.603)
Zinc	-1.611	(0.637)	0.303	(0.899)	0.281	(0.878)
Lead	3.442	(0.293)	3.572	(0.116)	**3.778**	**(0.030)**
Tin	5.547	(0.742)	5.308	(0.651)	3.597	(0.690)
Alum Alloy	-9.611	(0.111)	-4.191	(0.320)	-2.491	(0.442)
			\$1,000 Barriers			
Copper	-8.979	(0.244)	-5.008	(0.351)	**-9.242**	**(0.024)**
Alum	**-23.295**	**(0.030)**	**-26.356**	**(0.000)**	**-27.747**	**(0.000)**
Nickel	-1.611	(0.635)	-3.067	(0.192)	0.281	(0.877)
Zinc	**97.126**	**(0.000)**	**82.734**	**(0.000)**	**60.679**	**(0.000)**
Lead	9.547	(0.589)	-0.412	(0.973)	-9.061	(0.337)
Tin	**-7.084**	**(0.090)**	**-6.336**	**(0.029)**	**-4.661**	**(0.036)**
Alum Alloy	**-28.979**	**(0.032)**	**-29.012**	**(0.002)**	**-30.580**	**(0.000)**

Barrier proximity test is $f(M) = \alpha + \beta D^i + \varepsilon$, where $f(M)$ is the absolute frequency of digits. M is the set of all digits $\{0, \ldots, 99\}$. 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. For the \$100 barriers we are concerned with the two digits to the immediate left of the decimal point (-,-xx.–) and for the \$1,000 barriers we are concerned with the second and third digits to the left of the decimal point (-,xx-.–). Under the null of no barriers β will be zero, whereas the presence of barriers will result in a higher frequency of M-values at the barrier and thus β will be positive and significant. Results significant at the traditional 1%, 5% and 10% significance levels are bolded for emphasis, while results significant under the more statistically robust generalised Bonferroni multiple comparisons correction (p-value $<$ 0.00503; see Section 4) are underlined.

Table 2: Barrier Proximity Tests

	γ	(p-value)	γ	(p-value)
	$100 Barriers		$1,000 Barriers	
Copper	-0.001	(0.236)	**-0.007**	**(0.000)**
Alum	0.001	(0.403)	**-0.022**	**(0.000)**
Nickel	0.000	(0.972)	0.000	(0.914)
Zinc	-0.001	(0.297)	**0.042**	**(0.000)**
Lead	**0.003**	**(0.001)**	**-0.017**	**(0.001)**
Tin	0.000	(0.934)	-0.001	(0.435)
Alum Alloy	-0.002	(0.174)	**-0.013**	**(0.000)**

Barrier kurtosis test is $f(M) = \alpha + \varphi M + \gamma M^2 + \varepsilon$, where $f(M)$ is the absolute frequency of digits. M is the set of all digits $\{0, \ldots, 99\}$. For the $100 barriers we are concerned with the two digits to the immediate left of the decimal point (-,-xx.–) and for the $1,000 barriers we are concerned with the second and third digits to the left of the decimal point (-,xx-.–). 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 and clustering would be shown in a significant positive coefficient. Results significant at the traditional 1%, 5% and 10% significance levels are bolded for emphasis, while results significant under the more statistically robust generalised Bonferroni multiple comparisons correction (p-value $<$ 0.00507; see Section 4) are underlined.

Table 3: Barrier Kurtosis Tests

are supportive of clustering in non-ferrous metals being similar to the negative clustering found by Aggarwal and Lucey (2007) in gold markets.

The barrier kurtosis tests in Table 3 test for significant abnormal frequency distributions in the metals pricing series. The tests show that, once again, the $100 barrier level is not an important psychological barrier region with the exception of lead, but for the $1,000 barrier tests there is even stronger evidence of clustering under these more robust tests. Five of the seven series show evidence of clustering in the frequency distributions for the $1,000 level, with zinc showing positive clustering around psychological barrier regions, and copper, aluminium, lead, and aluminium alloy showing negative clustering. Importantly, all the findings are robust to generalised Bonferroni corrections to the p-values.

The price clustering analysis provides an initial investigation of the presence of behavioral influences on metals prices, but lacks a trading implication. The conditional effects tests for the full sample reported in Tables 4-10 allow an investigation of how prices react conditional on a barrier being breached. Barrier windows from one to ten days around a barrier breach are reported. Of most interest from these results are the AUB and ADB variables as these report price direction after an upward (AUB) or downward (ADB) breach of a barrier. Summarizing the findings, once again it is seen that the $1,000 barrier breach is more relevant than the $100 barrier, with the majority of significant coefficients following a barrier breach being for the $1,000 level. All of the metals report at least one significant coefficient after a $1,000 barrier breach (24 coefficients in total are significant across the different reaction windows for each metal), with 42 percent of the significant coefficients being after a downward breach and the remaining 58 percent after an upward breach. 63 percent of significant price reactions are in the first three days, and 92 percent in the first week. The general lack of significance for the two week window suggests that this is too long a time period to capture the temporal impact of a psychological barrier event.

When coefficients are confined to just those that are significant and robust to the generalized Bonferroni correction, only lead, zinc, and aluminium alloy remain to show significant price reactions, and only six coefficients for AUB and ADB meet this criteria, showing the importance of the correction technique in preventing any overstatement of the findings. With this robustness filter price movements after an upward breach of a barrier are shown to be a stronger trend compared to after downward breaches, with five of the six significant coefficients being for upward breaches, and lead, zinc, and aluminium alloy each having at least one significant reaction window after such an upward breach.

Turning attention now to the findings for the individual metals, it is noted first for aluminium alloy in Table 10 that there is just one generalised Bonferroni significant coefficient; for the day immediately after an upward breach of a $1,000 barrier. This shows that on

Barrier	$100						$1,000					
Reaction Wdw (n days)	1	2	3	4	5	10	1	2	3	4	5	10
Constant	0.000	0.000	0.001	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.268)	(0.224)	(0.091)	(0.257)	(0.578)	(0.773)	(0.204)	(0.259)	(0.166)	(0.153)	(0.113)	(0.233)
R_{t-1}	-0.065	-0.050	-0.038	-0.041	-0.046	-0.044	-0.046	-0.037	-0.039	-0.042	-0.041	-0.044
	(0.001)	(0.002)	(0.013)	(0.005)	(0.002)	(0.002)	(0.002)	(0.013)	(0.007)	(0.003)	(0.004)	(0.002)
BDB_t^n	0.001	**0.001**	**0.001**	0.001	0.000	0.000	-0.001	0.000	0.000	0.000	-0.001	**-0.001**
	(0.13)	**(0.066)**	**(0.058)**	(0.203)	(0.887)	(0.911)	(0.691)	(0.814)	(0.883)	(0.983)	(0.197)	**(0.085)**
BUB_t^n	**-0.001**	**-0.001**	**-0.001**	-0.001	0.000	0.000	**-0.004**	**-0.003**	**-0.002**	**-0.002**	-0.001	0.000
	(0.075)	**(0.026)**	**(0.01)**	(0.132)	(0.865)	(0.514)	**(0.008)**	**(0.018)**	**(0.018)**	**(0.037)**	(0.512)	(0.586)
ADB_t^n	-0.001	0.000	0.000	0.000	0.000	-0.001	0.001	**0.002**	**0.002**	0.001	0.001	0.000
	(0.22)	(0.413)	(0.791)	(0.977)	(0.46)	(0.151)	(0.528)	**(0.033)**	**(0.096)**	(0.473)	(0.51)	(0.824)
AUB_t^n	0.001	0.000	-0.001	0.000	0.001	0.001	**0.003**	0.000	0.000	0.000	0.000	0.001
	(0.331)	(0.689)	(0.263)	(0.712)	(0.307)	(0.339)	**(0.073)**	(0.962)	(0.981)	(0.633)	(0.97)	(0.293)

The test of conditional effects model is $R_t = \beta_0 + \beta_1 R_{t-1} + \beta_2 BDB_t^n + \beta_3 ADB_t^n + \beta_4 BUB_t^n + \beta_5 AUB_t^n + \varepsilon_t$, where$BDB^n$ is a dummy that assigns 1 to the n days *before* a downward breach, ADB^n is a dummy that assigns 1 to the n days *after* a downward breach, BUB^n is a dummy that assigns 1 to the n days *before* an upward breach and $AUB^n$is a dummy that assigns 1 to the n days *after* an upward breach. To test the speed of market reaction to barrier breaches, a range of reaction windows of size n days is considered. We choose $n = 1, 2, 3, 4, 5$ and 10 days, which allows us to assess the speed of market reaction over and up to 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. Note that p-values are given in parentheses. Results significant at the traditional 1%, 5% and 10% significance levels are bolded for emphasis, while results significant under the more statistically robust generalised Bonferroni multiple comparisons correction (p-value < 0.00503; see Section 4) are underlined.

Table 4: Tests of Conditional Effects: Copper

Barrier	$100						$1,000					
Reaction Wdw (n days)	1	2	3	4	5	10	1	2	3	4	5	10
Constant	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.706)	(0.899)	(0.861)	(0.867)	(0.808)	(0.884)	(0.657)	(0.738)	(0.726)	(0.618)	(0.696)	(0.633)
R_{t-1}	-0.008	-0.008	-0.009	-0.012	-0.017	-0.020	-0.011	-0.012	-0.014	-0.015	-0.016	-0.017
	(0.63)	(0.597)	(0.539)	(0.405)	(0.253)	(0.153)	(0.443)	(0.384)	(0.326)	(0.279)	(0.264)	(0.226)
BDB_t^n	0.001	**0.001**	**0.001**	**0.001**	**0.001**	0.000	-0.001	0.000	**0.003**	0.000	-0.001	-0.001
	(0.21)	**(0.052)**	**(0.009)**	**<u>(0.001)</u>**	**(0.006)**	(0.385)	(0.576)	(0.883)	**(0.077)**	(0.858)	(0.527)	(0.355)
BUB_t^n	0.001	0.000	0.000	0.000	0.001	**0.001**	0.001	0.000	0.000	0.002	0.002	0.001
	(0.203)	(0.587)	(0.789)	(0.743)	(0.209)	**(0.036)**	(0.638)	(0.874)	(0.974)	(0.242)	(0.212)	(0.286)
ADB_t^n	0.000	0.000	0.000	0.000	0.000	**-0.001**	0.004	**0.003**	0.001	0.000	0.000	-0.001
	(0.653)	(0.671)	(0.981)	(0.674)	(0.259)	**(0.04)**	(0.126)	**(0.056)**	(0.447)	(0.907)	(0.853)	(0.431)
AUB_t^n	**-0.001**	-0.001	**-0.001**	**-0.001**	**-0.001**	0.000	-0.002	-0.002	-0.002	-0.002	0.000	0.001
	(0.093)	(0.15)	**(0.018)**	**(0.008)**	**(0.085)**	(0.443)	(0.398)	(0.341)	(0.11)	(0.204)	(0.728)	(0.49)

The test of conditional effects model is $R_t = \beta_0 + \beta_1 R_{t-1} + \beta_2 BDB_t^n + \beta_3 ADB_t^n + \beta_4 BUB_t^n + \beta_5 AUB_t^n + \varepsilon_t$, where$BDB^n$ is a dummy that assigns 1 to the n days *before* a downward breach, ADB^n is a dummy that assigns 1 to the n days *after* a downward breach, BUB^n is a dummy that assigns 1 to the n days *before* an upward breach and $AUB^n$is a dummy that assigns 1 to the n days *after* an upward breach. To test the speed of market reaction to barrier breaches, a range of reaction windows of size n days is considered. We choose $n = 1, 2, 3, 4, 5$ and 10 days, which allows us to assess the speed of market reaction over and up to 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. Note that p-values are given in parentheses. Results significant at the traditional 1%, 5% and 10% significance levels are bolded for emphasis, while results significant under the more statistically robust robust generalised Bonferroni multiple comparisons correction (p-value $<$ 0.00503; see Section 4) are underlined.

Table 5: Tests of Conditional Effects: Aluminium

Barrier	$100						$1,000					
Reaction Wdw (n days)	1	2	3	4	5	10	1	2	3	4	5	10
Constant	-0.001	0.002	0.001	0.002	0.003	0.004	0.001	0.001	0.001	0.001	0.001	0.001
	(0.5)	(0.111)	(0.221)	(0.178)	(0.1)	(0.436)	(0.184)	(0.227)	(0.166)	(0.176)	(0.274)	(0.226)
R_{t-1}	-0.008	0.013	0.019	0.018	0.013	0.012	0.008	0.018	0.018	0.011	0.008	0.009
	(0.722)	(0.429)	(0.212)	(0.207)	(0.368)	(0.378)	(0.666)	(0.266)	(0.234)	(0.443)	(0.574)	(0.513)
BDB_t^n	**0.002**	0.001	**0.001**	0.001	0.001	0.000	0.000	0.001	**0.001**	0.000	0.000	-0.001
	(0.046)	(0.165)	**(0.068)**	(0.196)	(0.398)	(0.887)	(0.841)	(0.342)	**(0.064)**	(0.893)	(0.786)	(0.294)
BUB_t^n	0.000	**-0.002**	**-0.002**	-0.001	-0.002	-0.002	0.001	0.000	-0.001	-0.001	0.000	0.001
	(0.647)	**(0.006)**	**(0.024)**	(0.104)	(0.111)	(0.388)	(0.397)	(0.998)	(0.137)	(0.483)	(0.56)	(0.219)
ADB_t^n	0.000	-0.001	0.000	0.000	-0.001	0.000	**-0.002**	-0.001	0.000	-0.001	-0.001	**-0.001**
	(0.754)	(0.457)	(0.935)	(0.99)	(0.378)	(0.968)	**(0.046)**	(0.496)	(0.824)	(0.473)	(0.111)	**(0.073)**
AUB_t^n	0.001	-0.001	**-0.001**	**-0.002**	-0.001	-0.001	-0.002	**-0.002**	**-0.002**	0.000	0.000	0.000
	(0.3)	(0.319)	**(0.088)**	**(0.04)**	(0.184)	(0.784)	(0.183)	**(0.058)**	**(0.053)**	(0.718)	(0.883)	(0.691)

The test of conditional effects model is $R_t = \beta_0 + \beta_1 R_{t-1} + \beta_2 BDB_t^n + \beta_3 ADB_t^n + \beta_4 BUB_t^n + \beta_5 AUB_t^n + \varepsilon_t$, where$BDB^n$ is a dummy that assigns 1 to the n days *before* a downward breach, ADB^n is a dummy that assigns 1 to the n days *after* a downward breach, BUB^n is a dummy that assigns 1 to the n days *before* an upward breach and $AUB^n$is a dummy that assigns 1 to the n days *after* an upward breach. To test the speed of market reaction to barrier breaches, a range of reaction windows of size n days is considered. We choose $n = 1, 2, 3, 4, 5$ and 10 days, which allows us to assess the speed of market reaction over and up to 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. Note that p-values are given in parentheses. Results significant at the traditional 1%, 5% and 10% significance levels are bolded for emphasis, while results significant under the more statistically robust robust generalised Bonferroni multiple comparisons correction (p-value $<$ 0.00503; see Section 4) are underlined.

Table 6: Tests of Conditional Effects: Nickel

Barrier	$100						$1,000					
Reaction Wdw (n days)	1	2	3	4	5	10	1	2	3	4	5	10
Constant	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.456)	(0.302)	(0.273)	(0.349)	(0.637)	(0.57)	(0.517)	(0.54)	(0.63)	(0.615)	(0.635)	(0.604)
R_{t-1}	-0.052	-0.019	-0.017	-0.021	-0.018	-0.021	-0.025	-0.023	-0.023	-0.022	-0.023	-0.021
	(0.005)	(0.237)	(0.262)	(0.151)	(0.212)	(0.137)	(0.078)	(0.108)	(0.1)	(0.125)	(0.104)	(0.142)
BDB_t^n	0.000	0.001	0.001	0.000	0.000	0.000	**-0.007**	**-0.004**	-0.002	**-0.003**	**-0.004**	**-0.003**
	(0.961)	(0.36)	(0.323)	(0.946)	(0.549)	(0.513)	**(0.032)**	**(0.097)**	(0.247)	**(0.081)**	**(0.038)**	**(0.017)**
BUB_t^n	0.000	0.000	0.000	0.000	0.000	0.000	**-0.006**	-0.001	-0.003	-0.002	-0.001	0.002
	(0.795)	(0.541)	(0.494)	(0.813)	(0.663)	(0.666)	**(0.076)**	(0.678)	(0.214)	(0.345)	(0.545)	(0.241)
ADB_t^n	**-0.003**	-0.001	0.000	0.000	0.000	-0.001	-0.002	-0.001	0.000	0.001	0.000	0.000
	(0.01)	(0.432)	(0.634)	(0.489)	(0.922)	(0.315)	(0.497)	(0.577)	(0.822)	(0.518)	(0.957)	(0.96)
AUB_t^n	0.001	-0.001	-0.001	0.000	0.000	0.001	**0.010**	**0.004**	**0.006**	**0.004**	**0.005**	0.002
	(0.146)	(0.366)	(0.24)	(0.995)	(0.683)	(0.406)	**<u>(0.002)</u>**	**(0.061)**	**<u>(0.003)</u>**	**(0.032)**	**<u>(0.003)</u>**	(0.225)

The test of conditional effects model is $R_t = \beta_0 + \beta_1 R_{t-1} + \beta_2 BDB_t^n + \beta_3 ADB_t^n + \beta_4 BUB_t^n + \beta_5 AUB_t^n + \varepsilon_t$, where$BDB^n$ is a dummy that assigns 1 to the n days *before* a downward breach, ADB^n is a dummy that assigns 1 to the n days *after* a downward breach, BUB^n is a dummy that assigns 1 to the n days *before* an upward breach and $AUB^n$is a dummy that assigns 1 to the n days *after* an upward breach. To test the speed of market reaction to barrier breaches, a range of reaction windows of size n days is considered. We choose $n = 1, 2, 3, 4, 5$ and 10 days, which allows us to assess the speed of market reaction over and up to 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. Note that p-values are given in parentheses. Results significant at the traditional 1%, 5% and 10% significance levels are bolded for emphasis, while results significant under the more statistically robust robust generalised Bonferroni multiple comparisons correction (p-value $<$ 0.00503; see Section 4) are underlined.

Table 7: Tests of Conditional Effects: Zinc

Barrier	$100						$1,000					
Reaction Wdw (n days)	1	2	3	4	5	10	1	2	3	4	5	10
Constant	0.001	0.001	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.13)	(0.123)	(0.218)	(0.188)	(0.33)	(0.721)	(0.301)	(0.302)	(0.302)	(0.235)	(0.258)	(0.255)
R_{t-1}	0.052	0.051	0.059	0.056	0.060	0.050	0.050	0.046	0.047	0.048	0.046	0.050
	(0.004)	(0.001)	(0)	(0)	(0)	(0)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0)
BDB_t^n	-0.001	0.000	**0.001**	**0.002**	**0.001**	0.001	-0.004	**-0.006**	-0.001	-0.003	-0.001	-0.002
	(0.382)	(0.74)	**(0.05)**	**(0.021)**	**(0.067)**	(0.44)	(0.186)	**(0.014)**	(0.736)	(0.114)	(0.698)	(0.297)
BUB_t^n	0.001	0.000	0.000	-0.001	0.000	0.001	-0.003	**-0.006**	**-0.007**	**-0.005**	**-0.007**	**-0.003**
	(0.124)	(0.817)	(0.753)	(0.129)	(0.692)	(0.243)	(0.399)	**(0.013)**	**(0.001)**	**(0.004)**	**(0)**	**(0.082)**
ADB_t^n	-0.001	-0.001	0.000	0.000	0.001	-0.001	0.002	0.003	0.003	**0.003**	**0.004**	**0.005**
	(0.206)	(0.418)	(0.982)	(0.729)	(0.157)	(0.498)	(0.525)	(0.25)	(0.162)	**(0.064)**	**(0.034)**	**(0.004)**
AUB_t^n	-0.002	-0.001	**-0.002**	**-0.001**	**-0.002**	-0.001	0.003	**0.008**	**0.004**	0.003	**0.003**	-0.001
	(0.157)	(0.366)	**(0.013)**	**(0.042)**	**(0.002)**	(0.329)	(0.299)	**(0.001)**	**(0.048)**	(0.126)	**(0.063)**	(0.567)

The test of conditional effects model is $R_t = \beta_0 + \beta_1 R_{t-1} + \beta_2 BDB_t^n + \beta_3 ADB_t^n + \beta_4 BUB_t^n + \beta_5 AUB_t^n + \varepsilon_t$, where$BDB^n$ is a dummy that assigns 1 to the n days *before* a downward breach, ADB^n is a dummy that assigns 1 to the n days *after* a downward breach, BUB^n is a dummy that assigns 1 to the n days *before* an upward breach and $AUB^n$is a dummy that assigns 1 to the n days *after* an upward breach. To test the speed of market reaction to barrier breaches, a range of reaction windows of size n days is considered. We choose $n = 1, 2, 3, 4, 5$ and 10 days, which allows us to assess the speed of market reaction over and up to 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. Note that p-values are given in parentheses. Results significant at the traditional 1%, 5% and 10% significance levels are bolded for emphasis, while results significant under the more statistically robust robust generalised Bonferroni multiple comparisons correction (p-value $<$ 0.00503; see Section 4) are underlined.

Table 8: Tests of Conditional Effects: Lead

Barrier	$100						$1,000					
Reaction Wdw (n days)	1	2	3	4	5	10	1	2	3	4	5	10
Constant	0.000	0.000	0.000	0.000	0.000	-0.001	0.001	0.001	0.001	0.001	0.001	0.000
	(0.544)	(0.467)	(0.873)	(0.88)	(0.823)	(0.351)	(0.024)	(0.034)	(0.07)	(0.053)	(0.08)	(0.419)
R_{t-1}	0.005	0.031	0.027	0.028	0.024	0.021	0.015	0.020	0.032	0.026	0.024	0.020
	(0.802)	(0.061)	(0.077)	(0.056)	(0.089)	(0.13)	(0.372)	(0.205)	(0.034)	(0.075)	(0.101)	(0.158)
BDB_t^n	-0.001	0.000	**0.001**	**0.001**	0.001	0.001	-0.001	0.000	**0.001**	0.001	0.001	0.000
	(0.255)	(0.345)	**(0.028)**	**(0.012)**	(0.149)	(0.259)	(0.312)	(0.88)	**(0.078)**	(0.301)	(0.114)	(0.583)
BUB_t^n	-0.001	**-0.001**	-0.001	**-0.001**	-0.001	0.000	-0.001	0.000	-0.001	-0.001	-0.001	0.000
	(0.233)	**(0.086)**	(0.143)	**(0.068)**	(0.358)	(0.915)	(0.345)	(0.727)	(0.103)	(0.166)	(0.175)	(0.737)
ADB_t^n	0.000	0.001	0.000	0.001	0.000	0.000	**-0.002**	-0.001	0.000	0.000	0.000	-0.001
	(0.732)	(0.26)	(0.401)	(0.239)	(0.426)	(0.605)	**(0.093)**	(0.121)	(0.517)	(0.905)	(0.798)	(0.298)
AUB_t^n	**0.001**	0.000	0.000	-0.001	0.000	0.001	-0.001	-0.001	-0.002	-0.001	-0.001	0.001
	(0.055)	(0.694)	(0.534)	(0.313)	(0.883)	(0.184)	(0.539)	(0.292)	(0.022)	(0.152)	(0.26)	(0.381)

The test of conditional effects model is $R_t = \beta_0 + \beta_1 R_{t-1} + \beta_2 BDB_t^n + \beta_3 ADB_t^n + \beta_4 BUB_t^n + \beta_5 AUB_t^n + \varepsilon_t$, where$BDB^n$ is a dummy that assigns 1 to the n days *before* a downward breach, ADB^n is a dummy that assigns 1 to the n days *after* a downward breach, BUB^n is a dummy that assigns 1 to the n days *before* an upward breach and $AUB^n$is a dummy that assigns 1 to the n days *after* an upward breach. To test the speed of market reaction to barrier breaches, a range of reaction windows of size n days is considered. We choose $n = 1, 2, 3, 4, 5$ and 10 days, which allows us to assess the speed of market reaction over and up to 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. Note that p-values are given in parentheses. Results significant at the traditional 1%, 5% and 10% significance levels are bolded for emphasis, while results significant under the more statistically robust robust generalised Bonferroni multiple comparisons correction (p-value $<$ 0.00503; see Section 4) are underlined.

Table 9: Tests of Conditional Effects: Tin

Barrier	$100						$1,000					
Reaction Wdw (n days)	1	2	3	4	5	10	1	2	3	4	5	10
Constant	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.416)	(0.478)	(0.585)	(0.22)	(0.499)	(0.916)	(0.437)	(0.503)	(0.496)	(0.45)	(0.438)	(0.478)
R_{t-1}	-0.083	-0.075	-0.081	-0.082	-0.087	-0.085	-0.070	-0.079	-0.078	-0.077	-0.080	-0.083
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
BDB_t^n	**0.002**	**0.001**	0.001	0.000	0.000	0.000	**0.014**	**0.008**	**0.006**	0.003	0.001	-0.001
	(0.001)	**(0.04)**	(0.19)	(0.854)	(0.569)	(0.939)	**(<u>0</u>)**	**(<u>0.001</u>)**	**(<u>0.004</u>)**	(0.173)	(0.619)	(0.649)
BUB_t^n	-0.001	-0.001	0.000	0.000	0.000	**0.001**	**-0.005**	-0.001	-0.001	0.000	0.002	**0.003**
	(0.142)	(0.095)	(0.535)	(0.946)	(0.446)	**(0.02)**	**(0.065)**	(0.597)	(0.559)	(0.847)	(0.317)	**(0.082)**
ADB_t^n	-0.001	0.000	0.000	0.000	**-0.001**	**-0.001**	0.004	0.001	0.001	0.002	0.001	-0.002
	(0.209)	(0.658)	(0.723)	(0.265)	**(0.043)**	**(0.057)**	(0.202)	(0.699)	(0.777)	(0.201)	(0.774)	(0.198)
AUB_t^n	-0.001	0.000	0.000	0.000	0.000	0.000	**-0.012**	**-0.004**	-0.003	**-0.005**	**-0.003**	0.001
	(0.425)	(0.368)	(0.926)	(0.659)	(0.614)	(0.825)	**(<u>0</u>)**	**(0.055)**	(0.111)	**(0.011)**	**(0.099)**	(0.735)

The test of conditional effects model is $R_t = \beta_0 + \beta_1 R_{t-1} + \beta_2 BDB_t^n + \beta_3 ADB_t^n + \beta_4 BUB_t^n + \beta_5 AUB_t^n + \varepsilon_t$, where$BDB^n$ is a dummy that assigns 1 to the n days *before* a downward breach, ADB^n is a dummy that assigns 1 to the n days *after* a downward breach, BUB^n is a dummy that assigns 1 to the n days *before* an upward breach and $AUB^n$is a dummy that assigns 1 to the n days *after* an upward breach. To test the speed of market reaction to barrier breaches, a range of reaction windows of size n days is considered. We choose $n = 1, 2, 3, 4, 5$ and 10 days, which allows us to assess the speed of market reaction over and up to 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. Note that p-values are given in parentheses. Results significant at the traditional 1%, 5% and 10% significance levels are bolded for emphasis, while results significant under the more statistically robust robust generalised Bonferroni multiple comparisons correction (p-value $<$ 0.00503; see Section 4) are underlined.

Table 10: Tests of Conditional Effects: Aluminium Alloy

average there is a 1.2 percent price retrenchment after such a breach, clearly an economically significant event. In contrast, both lead and zinc demonstrate price momentum after an upward breach, with each showing significantly positive coefficients. The only significant coefficient for after a downward breach of the $1,000 level is for lead, where the 10-day window shows price retrenchment after a breach.

Expanding the analysis thus far, the subperiods tests reported in Tables 11-17 confine testing to just the 1-day, 2-day, and 3-day windows, which were shown to be most important in the overall psychological barrier tests. One overall finding is that $1,000 barriers appear to be most important in the most recent subperiod, and $100 were more important in the earlier subperiod. For example, 85 percent (11 of 13) of significant $1,000 barrier coefficients are in the second period from December 2003 to December 2013. This was a time in the market when there was significant price moves upwards and downwards through $1,000 levels for many of the metals. There are significant barrier coefficients for five of the seven metals in this subperiod, but only for two metals in the earliest subperiod. However, the strength of the findings is weaker in the subperiods analysis compared to the overall analysis, as only aluminum alloy is significant under the generalized Bonferroni correction. The $100 barriers, which were largely absent in the overall analysis, are more prominent in the subperiods analysis. There are now 14 significant barrier coefficients for $100 across the seven metals and three different day ranges. Five of the seven metals show significant barriers in the early subperiod, and three in the most recent subperiod. Three of the metals have barrier coefficient p-values that are robust to the generalised Bonferroni correction: aluminium and tin in the first subperiod, and copper in the second subperiod, with all showing price retrenchment after passing through a $100 barrier through rising prices.

Overall, the particularly interesting feature of the subperiods findings is how the importance of particular barriers appears to shift depending on market price levels; with $100 barriers mattering more in the earlier low price range regimes and $1,000 barriers mattering more in the most recent high price range regimes.

6 Conclusion

The absence of behavioral-based research in the non-ferrous metals markets is difficult to justify, given the increased reward from applying the theories of this research area to other professionally-traded markets, such as oil, gold, and foreign exchange. This study represents a first attempt to apply such a behavioral perspective to the non-ferrous metals markets. With the application of a generalized Bonferroni correction to account for the multiple hypothesis testing nature of the investigation, it can be concluded with statistical confidence that the non-ferrous metals markets are not immune to behavioral influence. Specifically, there is evidence of price clustering before key psychological price points for five of the seven non-ferrous metals studied. This usually takes the form of negative clustering (for copper, aluminium, lead, and aluminium alloy), similar to previous findings in the gold markets by Aggarwal and Lucey (2007), and indicating that there is a below-expected frequency distribution in barrier regions around $1,000 price levels. Zinc, however, shows positive clustering in barrier regions. For traders the general implication is that prices show a reluctance to pass key psychological price regions.

It is further shown that prices tend towards a predictable directional movement once they pass a psychological price barrier for a number of the metals. Aluminium alloy retrenches on average by 1.2 percent in the day after rising through a $1,000 barrier. Lead and zinc show price momentum in the days after rising through the same barrier level. In addition

Barrier	$100						$1,000					
Period	Subperiod 1: Dec 1993-Nov 2003			Subperiod 2: Dec 2003-Dec 2013			Subperiod 1: Dec 1993-Nov 2003			Subperiod 2: Dec 2003-Dec 2013		
Reaction Wdw (n days)	1	2	3	1	2	3	1	2	3	1	2	3
Constant	0.000	0.000	0.000	0.002	0.003	0.005	0.000	0.000	0.000	0.001	0.001	0.001
	(0.537)	(0.392)	(0.232)	(0.014)	(0.005)	(0)	(0.787)	(0.895)	(0.749)	(0.16)	(0.182)	(0.118)
R_{t-1}	0.041	0.046	0.053	-0.101	-0.072	-0.065	0.041	0.042	0.044	-0.087	-0.072	-0.076
	(0.086)	(0.041)	(0.014)	(0.002)	(0.002)	(0.002)	(0.039)	(0.035)	(0.028)	(0)	(0.001)	(0)
BDB_t^n	**-0.002**	0.000	0.001	**0.002**	0.001	0.001	-0.004	0.000	-0.001	0.000	0.000	0.000
	(0.096)	(0.831)	(0.356)	**(0.079)**	(0.144)	(0.246)	(0.181)	(0.889)	(0.654)	(0.884)	(0.955)	(0.928)
BUB_t^n	**0.002**	0.000	0.000	**-0.003**	**-0.003**	**-0.004**	0.001	0.001	-0.002	**-0.005**	**-0.003**	**-0.003**
	(0.046)	(0.625)	(0.516)	**(0.004)**	**(0)**	**(0)**	(0.64)	(0.78)	(0.392)	**(0.008)**	**(0.022)**	**(0.044)**
ADB_t^n	-0.001	-0.001	0.000	-0.002	0.000	0.000	-0.001	0.000	0.001	0.000	0.002	0.001
	(0.315)	(0.407)	(0.805)	(0.037)	(0.58)	(0.88)	(0.793)	(0.912)	(0.534)	(0.904)	(0.113)	(0.361)
AUB_t^n	0.000	-0.001	**-0.001**	-0.001	**-0.002**	**-0.003**	0.004	0.002	0.001	0.003	0.000	0.000
	(0.628)	(0.303)	**(0.029)**	(0.313)	**(0.058)**	**(0.003)**	(0.11)	(0.309)	(0.516)	(0.14)	(0.901)	(0.899)

The test of conditional effects model is $R_t = \beta_0 + \beta_1 R_{t-1} + \beta_2 BDB_t^n + \beta_3 ADB_t^n + \beta_4 BUB_t^n + \beta_5 AUB_t^n + \varepsilon_t$, where$BDB^n$ is a dummy that assigns 1 to the n days *before* a downward breach, ADB^n is a dummy that assigns 1 to the n days *after* a downward breach, BUB^n is a dummy that assigns 1 to the n days *before* an upward breach and $AUB^n$is a dummy that assigns 1 to the n days *after* an upward breach. To test the speed of market reaction to barrier breaches, a range of reaction windows of size n days is considered. We choose $n = 1, 2, 3, 4, 5$ and 10 days, which allows us to assess the speed of market reaction over and up to 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. Note that p-values are given in parentheses. Results significant at the traditional 1%, 5% and 10% significance levels are bolded for emphasis, while results significant under the more statistically robust generalised Bonferroni multiple comparisons correction (p-value $<$ 0.00503; see Section 4) are underlined.

Table 11: Subperiod Tests of Conditional Effects: Copper

Barrier	$100						$1,000					
Period	Subperiod 1: Dec 1993-Nov 2003			Subperiod 2: Dec 2003-Dec 2013			Subperiod 1: Dec 1993-Nov 2003			Subperiod 2: Dec 2003-Dec 2013		
Reaction Wdw (n days)	1	2	3	1	2	3	1	2	3	1	2	3
Constant	0.000	0.000	0.000	0.000	0.001	0.001	0.000	0.000	0.000	0.000	0.000	0.000
	(0.37)	(0.934)	(0.393)	(0.585)	(0.12)	(0.141)	(0.446)	(0.534)	(0.542)	(0.986)	(0.942)	(0.965)
R_{t-1}	0.049	0.060	0.068	-0.077	-0.039	-0.044	0.047	0.050	0.050	-0.040	-0.043	-0.045
	(0.03)	(0.005)	(0.001)	(0.003)	(0.097)	(0.041)	(0.019)	(0.012)	(0.012)	(0.051)	(0.035)	(0.026)
BDB_t^n	-0.001	0.001	**0.001**	0.000	0.000	0.000	-0.002	-0.006	-0.003	-0.001	0.001	**0.003**
	(0.322)	(0.261)	**(0.065)**	(0.724)	(0.803)	(0.503)	(0.807)	(0.31)	(0.535)	(0.62)	(0.722)	**(0.088)**
BUB_t^n	0.001	0.000	0.000	**-0.002**	**-0.002**	**-0.002**	-0.009	0.005	0.005	0.001	0.000	0.000
	(0.508)	(0.8)	(0.398)	**(0.046)**	**<u>(0.001)</u>**	**<u>(0.004)</u>**	(0.303)	(0.443)	(0.41)	(0.601)	(0.953)	(0.911)
ADB_t^n	-0.001	0.001	0.001	-0.001	0.000	0.000	**-0.020**	0.004	0.005	0.004	0.003	0.001
	(0.519)	(0.171)	(0.145)	(0.25)	(0.602)	(0.892)	**(0.009)**	(0.483)	(0.337)	(0.116)	(0.147)	(0.69)
AUB_t^n	0.000	-0.001	**-0.002**	0.001	-0.001	-0.001	-0.002	-0.001	-0.004	-0.001	-0.001	-0.002
	(0.691)	(0.413)	**<u>(0.001)</u>**	(0.179)	(0.343)	(0.433)	(0.841)	(0.908)	(0.521)	(0.715)	(0.486)	(0.234)

The test of conditional effects model is $R_t = \beta_0 + \beta_1 R_{t-1} + \beta_2 BDB_t^n + \beta_3 ADB_t^n + \beta_4 BUB_t^n + \beta_5 AUB_t^n + \varepsilon_t$, where$BDB^n$ is a dummy that assigns 1 to the n days *before* a downward breach, ADB^n is a dummy that assigns 1 to the n days *after* a downward breach, BUB^n is a dummy that assigns 1 to the n days *before* an upward breach and $AUB^n$is a dummy that assigns 1 to the n days *after* an upward breach. To test the speed of market reaction to barrier breaches, a range of reaction windows of size n days is considered. We choose $n = 1, 2, 3, 4, 5$ and 10 days, which allows us to assess the speed of market reaction over and up to 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. Note that p-values are given in parentheses. Results significant at the traditional 1%, 5% and 10% significance levels are bolded for emphasis, while results significant under the more statistically robust robust generalised Bonferroni multiple comparisons correction (p-value $<$ 0.00503; see Section 4) are underlined.

Table 12: Subperiod Tests of Conditional Effects: Aluminium

Barrier	$100						$1,000					
Period	Subperiod 1: Dec 1993-Nov 2003			Subperiod 2: Dec 2003-Dec 2013			Subperiod 1: Dec 1993-Nov 2003			Subperiod 2: Dec 2003-Dec 2013		
Reaction Wdw (n days)	1	2	3	1	2	3	1	2	3	1	2	3
Constant	0.000	0.000	0.000	-0.001	0.004	0.004	0.000	0.000	0.000	0.001	0.001	0.001
	(0.608)	(0.8)	(0.781)	(0.742)	(0.054)	(0.144)	(0.281)	(0.299)	(0.323)	(0.405)	(0.478)	(0.309)
R_{t-1}	0.003	0.022	0.019	-0.003	0.019	0.024	0.021	0.024	0.021	-0.004	0.013	0.016
	(0.922)	(0.348)	(0.374)	(0.927)	(0.416)	(0.274)	(0.331)	(0.26)	(0.314)	(0.883)	(0.577)	(0.471)
BDB_t^n	**0.002**	**0.002**	**0.001**	0.002	0.000	0.001	-0.001	0.000	0.000	0.001	0.001	**0.002**
	(0.077)	**(0.035)**	**(0.063)**	(0.231)	(0.842)	(0.455)	(0.512)	(0.816)	(0.879)	(0.621)	(0.23)	**(0.079)**
BUB_t^n	0.000	0.000	0.000	0.000	**-0.003**	**-0.004**	-0.001	-0.002	-0.001	0.001	0.001	-0.001
	(0.685)	(0.517)	(0.658)	(0.92)	**<u>(0.005)</u>**	**(0.011)**	(0.772)	(0.153)	(0.279)	(0.322)	(0.457)	(0.383)
ADB_t^n	0.000	0.000	-0.001	0.000	0.000	0.001	0.000	0.001	0.000	**-0.003**	-0.001	0.000
	(0.738)	(0.548)	(0.318)	(0.819)	(0.792)	(0.454)	(0.827)	(0.617)	(0.883)	**(0.045)**	(0.266)	(0.657)
AUB_t^n	0.001	0.000	0.000	0.000	**-0.002**	**-0.003**	0.000	0.001	0.001	-0.002	**-0.003**	**-0.003**
	(0.469)	(0.604)	(0.731)	(0.951)	**(0.082)**	**(0.026)**	(0.857)	(0.666)	(0.582)	(0.23)	**(0.035)**	**(0.022)**

The test of conditional effects model is $R_t = \beta_0 + \beta_1 R_{t-1} + \beta_2 BDB_t^n + \beta_3 ADB_t^n + \beta_4 BUB_t^n + \beta_5 AUB_t^n + \varepsilon_t$, where$BDB^n$ is a dummy that assigns 1 to the n days *before* a downward breach, ADB^n is a dummy that assigns 1 to the n days *after* a downward breach, BUB^n is a dummy that assigns 1 to the n days *before* an upward breach and $AUB^n$is a dummy that assigns 1 to the n days *after* an upward breach. To test the speed of market reaction to barrier breaches, a range of reaction windows of size n days is considered. We choose $n = 1, 2, 3, 4, 5$ and 10 days, which allows us to assess the speed of market reaction over and up to 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. Note that p-values are given in parentheses. Results significant at the traditional 1%, 5% and 10% significance levels are bolded for emphasis, while results significant under the more statistically robust robust generalised Bonferroni multiple comparisons correction (p-value $<$ 0.00503; see Section 4) are underlined.

Table 13: Subperiod Tests of Conditional Effects: Nickel

Barrier	\$100						\$1,000					
Period	Subperiod 1: Dec 1993-Nov 2003			Subperiod 2: Dec 2003-Dec 2013			Subperiod 1: Dec 1993-Nov 2003			Subperiod 2: Dec 2003-Dec 2013		
Reaction Wdw (n days)	1	2	3	1	2	3	1	2	3	1	2	3
Constant	0.000	0.000	0.000	0.001	0.001	0.001	0.000	0.000	0.000	0.000	0.000	0.000
	(0.91)	(0.931)	(0.917)	(0.163)	(0.354)	(0.147)	(0.921)	(0.951)	(0.959)	(0.455)	(0.478)	(0.575)
R_{t-1}	-0.034	-0.009	-0.010	-0.010	-0.026	-0.017	-0.012	-0.008	-0.006	-0.030	-0.027	-0.028
	(0.116)	(0.673)	(0.638)	(0.724)	(0.265)	(0.435)	(0.568)	(0.693)	(0.761)	(0.134)	(0.177)	(0.166)
BDB_t^n	-0.001	0.001	0.001	0.002	0.001	0.001	-0.001	-0.001	0.000	-0.007	-0.004	-0.002
	(0.384)	(0.151)	(0.511)	(0.1)	(0.206)	(0.407)	(0.589)	(0.572)	(0.958)	(0.077)	(0.169)	(0.334)
BUB_t^n	0.002	0.001	0.000	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.006	-0.001	-0.003
	(0.124)	(0.251)	(0.649)	(0.352)	(0.476)	(0.113)	(0.749)	(0.612)	(0.472)	(0.146)	(0.717)	(0.305)
ADB_t^n	**-0.004**	-0.001	-0.001	-0.002	-0.001	0.000	0.001	0.002	0.002	-0.003	-0.002	-0.001
	(0.006)	(0.302)	(0.517)	(0.306)	(0.302)	(0.879)	(0.671)	(0.294)	(0.121)	(0.534)	(0.606)	(0.812)
AUB_t^n	0.002	-0.001	-0.001	**-0.003**	-0.001	-0.001	0.002	0.000	-0.001	**0.010**	0.004	**0.006**
	(0.183)	(0.218)	(0.405)	**(0.052)**	(0.552)	(0.227)	(0.304)	(0.842)	(0.505)	**(0.012)**	(0.136)	**(0.019)**

The test of conditional effects model is $R_t = \beta_0 + \beta_1 R_{t-1} + \beta_2 BDB_t^n + \beta_3 ADB_t^n + \beta_4 BUB_t^n + \beta_5 AUB_t^n + \varepsilon_t$, where$BDB^n$ is a dummy that assigns 1 to the n days *before* a downward breach, ADB^n is a dummy that assigns 1 to the n days *after* a downward breach, BUB^n is a dummy that assigns 1 to the n days *before* an upward breach and $AUB^n$is a dummy that assigns 1 to the n days *after* an upward breach. To test the speed of market reaction to barrier breaches, a range of reaction windows of size n days is considered. We choose $n = 1, 2, 3, 4, 5$ and 10 days, which allows us to assess the speed of market reaction over and up to 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. Note that p-values are given in parentheses. Results significant at the traditional 1%, 5% and 10% significance levels are bolded for emphasis, while results significant under the more statistically robust robust generalised Bonferroni multiple comparisons correction (p-value $<$ 0.00503; see Section 4) are underlined.

Table 14: Subperiod Tests of Conditional Effects: Zinc

Barrier	$100						$1,000					
Period	Subperiod 1: Dec 1993-Nov 2003			Subperiod 2: Dec 2003-Dec 2013			Subperiod 1: Dec 1993-Nov 2003*			Subperiod 2: Dec 2003-Dec 2013		
Reaction Wdw (n days)	1	2	3	1	2	3	1	2	3	1	2	3
Constant	0.000	0.000	0.000	0.001	0.001	0.001	-	-	-	0.000	0.000	0.000
	(0.776)	(0.675)	(0.735)	(0.13)	(0.154)	(0.324)	-	-	-	(0.365)	(0.363)	(0.36)
R_{t-1}	-0.005	0.013	0.017	0.047	0.060	0.060	-	-	-	0.062	0.057	0.058
	(0.827)	(0.543)	(0.399)	(0.084)	(0.012)	(0.007)	-	-	-	(0.002)	(0.005)	(0.004)
BDB_t^n	0.000	**0.002**	**0.002**	**-0.005**	**-0.003**	**-0.002**	-	-	-	-0.004	**-0.006**	-0.001
	(0.99)	**(0.072)**	**(0.092)**	**(0.001)**	**(0.002)**	**(0.072)**	-	-	-	(0.267)	**(0.04)**	(0.771)
BUB_t^n	**0.004**	0.000	-0.001	0.001	0.000	0.000	-	-	-	-0.003	**-0.006**	**-0.007**
	(0.016)	(0.803)	(0.584)	(0.668)	(0.882)	(0.733)	-	-	-	(0.482)	**(0.038)**	**(0.005)**
ADB_t^n	**-0.005**	-0.002	0.000	-0.001	0.000	0.000	-	-	-	0.002	0.003	0.003
	(0.004)	(0.217)	(0.976)	(0.599)	(0.826)	(0.936)	-	-	-	(0.556)	(0.324)	(0.238)
AUB_t^n	**0.003**	-0.001	-0.001	0.001	0.001	0.001	-	-	-	0.003	**0.008**	0.004
	(0.095)	(0.562)	(0.44)	(0.483)	(0.445)	(0.637)	-	-	-	(0.478)	**(0.007)**	(0.14)

The test of conditional effects model is $R_t = \beta_0 + \beta_1 R_{t-1} + \beta_2 BDB_t^n + \beta_3 ADB_t^n + \beta_4 BUB_t^n + \beta_5 AUB_t^n + \varepsilon_t$, where$BDB^n$ is a dummy that assigns 1 to the n days *before* a downward breach, ADB^n is a dummy that assigns 1 to the n days *after* a downward breach, BUB^n is a dummy that assigns 1 to the n days *before* an upward breach and $AUB^n$is a dummy that assigns 1 to the n days *after* an upward breach. To test the speed of market reaction to barrier breaches, a range of reaction windows of size n days is considered. We choose $n = 1, 2, 3, 4, 5$ and 10 days, which allows us to assess the speed of market reaction over and up to 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. Note that p-values are given in parentheses. Results significant at the traditional 1%, 5% and 10% significance levels are bolded for emphasis, while results significant under the more statistically robust robust generalised Bonferroni multiple comparisons correction (p-value < 0.00503; see Section 4) are underlined. * Lead did not trade above the $1000 barrier level during the period Dec 1993 - Nov 2003.

Table 15: Subperiod Tests of Conditional Effects: Lead

Barrier	$100						$1,000					
Period	Subperiod 1: Dec 1993-Nov 2003			Subperiod 2: Dec 2003-Dec 2013			Subperiod 1: Dec 1993-Nov 2003			Subperiod 2: Dec 2003-Dec 2013		
Reaction Wdw (n days)	1	2	3	1	2	3	1	2	3	1	2	3
Constant	0.000	0.000	0.000	0.000	0.002	0.002	0.000	0.000	0.000	0.001	0.002	0.002
	(0.868)	(0.686)	(0.551)	(0.785)	(0.277)	(0.206)	(0.558)	(0.7)	(0.767)	(0.012)	(0.01)	(0.018)
R_{t-1}	0.082	0.102	0.083	-0.011	0.005	0.003	0.065	0.061	0.066	-0.007	0.004	0.020
	(0.005)	(0)	(0)	(0.73)	(0.833)	(0.903)	(0.002)	(0.003)	(0.001)	(0.777)	(0.86)	(0.365)
BDB_t^n	-0.001	**0.001**	**0.001**	0.000	0.000	0.000	-0.002	0.002	**0.002**	-0.001	-0.001	0.001
	(0.133)	**(0.037)**	**(<u>0.001</u>)**	(0.862)	(0.78)	(0.716)	(0.39)	(0.244)	**(0.084)**	(0.289)	(0.603)	(0.489)
BUB_t^n	**0.001**	0.000	0.000	-0.001	**-0.002**	**-0.003**	0.000	0.001	0.001	-0.002	-0.001	**-0.002**
	(0.037)	(0.608)	(0.461)	(0.24)	**(0.026)**	**(0.017)**	(0.912)	(0.551)	(0.447)	(0.235)	(0.353)	**(0.04)**
ADB_t^n	0.000	0.001	**0.001**	0.000	0.000	-0.001	-0.001	-0.001	0.000	**-0.003**	**-0.002**	0.000
	(0.729)	(0.103)	**(0.052)**	(0.769)	(0.877)	(0.558)	(0.546)	(0.407)	(0.899)	**(0.054)**	**(0.09)**	(0.967)
AUB_t^n	-0.001	**-0.002**	**-0.001**	0.002	0.001	0.001	-0.002	-0.002	**-0.003**	0.000	-0.001	**-0.002**
	(0.455)	**(<u>0</u>)**	**(<u>0.004</u>)**	(0.161)	(0.461)	(0.524)	(0.227)	(0.136)	**(0.008)**	(0.728)	(0.405)	**(0.087)**

The test of conditional effects model is $R_t = \beta_0 + \beta_1 R_{t-1} + \beta_2 BDB_t^n + \beta_3 ADB_t^n + \beta_4 BUB_t^n + \beta_5 AUB_t^n + \varepsilon_t$, where$BDB^n$ is a dummy that assigns 1 to the n days *before* a downward breach, ADB^n is a dummy that assigns 1 to the n days *after* a downward breach, BUB^n is a dummy that assigns 1 to the n days *before* an upward breach and $AUB^n$is a dummy that assigns 1 to the n days *after* an upward breach. To test the speed of market reaction to barrier breaches, a range of reaction windows of size n days is considered. We choose $n = 1, 2, 3, 4, 5$ and 10 days, which allows us to assess the speed of market reaction over and up to 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. Note that p-values are given in parentheses. Results significant at the traditional 1%, 5% and 10% significance levels are bolded for emphasis, while results significant under the more statistically robust robust generalised Bonferroni multiple comparisons correction (p-value $<$ 0.00503; see Section 4) are underlined.

Table 16: Subperiod Tests of Conditional Effects: Tin

Barrier	$100						$1,000					
Period	Subperiod 1: Dec 1993-Nov 2003			Subperiod 2: Dec 2003-Dec 2013			Subperiod 1: Dec 1993-Nov 2003			Subperiod 2: Dec 2003-Dec 2013		
Reaction Wdw (n days)	1	2	3	1	2	3	1	2	3	1	2	3
Constant	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.321)	(0.463)	(0.556)	(0.844)	(0.672)	(0.879)	(0.442)	(0.426)	(0.416)	(0.747)	(0.861)	(0.858)
R_{t-1}	0.069	0.069	0.071	-0.134	-0.146	-0.148	0.067	0.065	0.064	-0.136	-0.147	-0.146
	(0.002)	(0.001)	(0.001)	(0)	(0)	(0)	(0.001)	(0.001)	(0.001)	(0)	(0)	(0)
BDB_t^n	-0.001	-0.001	-0.001	**0.004**	**0.003**	**0.001**	0.002	-0.001	-0.001	**0.016**	**0.009**	**0.007**
	(0.575)	(0.249)	(0.279)	**(0)**	**(0.001)**	**(0.077)**	(0.813)	(0.929)	(0.8)	**(0)**	**(0.001)**	**(0.008)**
BUB_t^n	0.001	0.001	0.000	**-0.003**	**-0.002**	-0.001	-0.006	-0.002	0.000	-0.005	-0.001	-0.001
	(0.326)	(0.223)	(0.458)	**(0.004)**	**(0.017)**	(0.152)	(0.354)	(0.768)	(0.94)	(0.214)	(0.83)	(0.688)
ADB_t^n	-0.001	0.000	0.001	0.001	0.000	0.000	0.010	0.000	-0.003	0.002	0.000	0.000
	(0.566)	(0.754)	(0.223)	(0.566)	(0.589)	(0.908)	(0.19)	(1)	(0.544)	(0.641)	(0.947)	(0.995)
AUB_t^n	-0.001	0.000	0.000	-0.001	0.000	0.000	-0.003	0.000	0.001	**-0.012**	**-0.005**	-0.003
	(0.234)	(0.591)	(0.523)	(0.396)	(0.759)	(0.658)	(0.636)	(0.933)	(0.878)	**(0.001)**	**(0.093)**	(0.257)

The test of conditional effects model is $R_t = \beta_0 + \beta_1 R_{t-1} + \beta_2 BDB_t^n + \beta_3 ADB_t^n + \beta_4 BUB_t^n + \beta_5 AUB_t^n + \varepsilon_t$, where$BDB^n$ is a dummy that assigns 1 to the n days *before* a downward breach, ADB^n is a dummy that assigns 1 to the n days *after* a downward breach, BUB^n is a dummy that assigns 1 to the n days *before* an upward breach and $AUB^n$is a dummy that assigns 1 to the n days *after* an upward breach. To test the speed of market reaction to barrier breaches, a range of reaction windows of size n days is considered. We choose $n = 1, 2, 3, 4, 5$ and 10 days, which allows us to assess the speed of market reaction over and up to 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. Note that p-values are given in parentheses. Results significant at the traditional 1%, 5% and 10% significance levels are bolded for emphasis, while results significant under the more statistically robust robust generalised Bonferroni multiple comparisons correction (p-value $<$ 0.00503; see Section 4) are underlined.

Table 17: Subperiod Tests of Conditional Effects: Aluminium Alloy

to the trading implications, this price predictability following a barrier breach represents a clear violation of weak-form market efficiency.

We also find that the relevant psychological barrier level appears to reference average market prices. Thus, $100 barriers mattered in the early low price range subperiod analysis from December 1993 to November 2003, while $1,000 mattered more in the most recent period from December 2003 to December 2013. This finding has implications for understanding the relevant psychological barrier levels for a particular market. Quite why some metals show different clustering and reactions to barrier breaches is not obvious, and evidence from other professionally traded markets suggests it might be due to institutional reasons unique to a particular market. This is worthy of further investigation, especially as these differences are also evident across other financial markets. More generally there is a need to extend the testing toolkit of non-ferrous metals markets prices to incorporate the behavioral principles that are bringing new understanding to pricing and trader decision making across the spectrum of professionally traded markets.

References

Aggarwal, R., Lucey, B.M., 2007. Psychological barriers in gold prices? Review of Financial Economics, 16(2), 217-230.

Batten, J. A., Ciner, C., & Lucey, B. M. (2010). The macroeconomic determinants of volatility in precious metals markets. Resources Policy, 35(2), 65-71.

Bharati, R., Crain, S.J., Kaminski, V., 2012. Clustering in crude oil prices and the target pricing zone hypothesis. Energy Economics, 34(4), 1115-1123.

Bhattacharya, U., Holden, C.W., Jacobsen, S., 2012. Penny wise, dollar foolish: Buy-sell imbalances on and around round numbers. Management Science, 58(2), 413-431.

Buncic, D., Moretto, C. 2014. Forecasting Copper Prices with Dynamic Averaging and Selection Models. Working Paper No. 1430: University of St. Gallen, School of Economics and Political Science.

Coakley, J., Dollery, J., Kellard, N., 2011. Long memory and structural breaks in commodity futures markets. Journal of Futures Markets, 31(11), 1076-1113.

Cochran, S.J., Mansur, I., Odusami, B., 2012. Volatility persistence in metal returns: a FIGARCH approach. Journal of Economics and Business, 64(4), 287-305.

Coval, J.D., Shumway, T., 2005. Do behavioral biases affect prices? Journal of Finance, 60(1), 1-34.

Cummins, M., 2013. EU ETS market interactions: The case for multiple hypothesis testing approaches. Applied Energy, 111, 701-709.

Donaldson, R.G., Kim, H.Y., 1993. Price barriers in the Dow Jones industrial average. Journal of Financial and Quantitative Analysis, 28(3), 313-330.

Dorfleitner, G., & Klein, C., 2009. Psychological barriers in European stock markets: Where are they? Global Finance Journal, 19(3), 268-285.

Dowling, M., Cummins, M., Lucey, B.M., 2014. Psychological barriers in oil futures markets. Energy Economics, forthcoming

Fama, E.F., 1998. Market efficiency, long-term returns, and behavioral finance. Journal of Financial Economics, 49(3), 283-306.

Harvey, C.R., Liu, Y., Zhu, H., ... and the Cross-Section of Expected Returns. Duke University, Working Paper (October 4, 2014). SSRN: http://ssrn.com/abstract=2249314

Heaney, R., 2006. An empirical analysis of commodity pricing. Journal of Futures Markets, 26(4), 391-415.

Hirshleifer, D.A., 2001. Investor psychology and asset pricing. The Journal of Finance, 56(4), 1533-1597.

Hirshleifer, D.A., 2014. Behavioral finance. University of California, Irvine, Working Paper (August 15, 2014). SSRN: http://ssrn.com/abstract=2480892

Ikenberry, D.L., Weston, J.P., 2008. Clustering in US stock prices after decimalisation. European Financial Management, 14(1), 30-54.

Mitchell J., 2001. Clustering and psychological barriers: the importance of numbers. Journal of Futures Markets, 21(5), 395-428.

Mitchell, J., Izan, H.Y., 2006. Clustering and psychological barriers in exchange rates. Journal of International Financial Markets, Institutions and Money, 16(4), 318-344.

Narayan, P.K., Narayan, S., Popp, S., 2011. Investigating price clustering in the oil futures market. Applied Energy, 88(1), 397–402.

Niederhoffer, V., 1965. Clustering of stock prices. Operations Research, 13(2), 258-265.

O'Connell, P.G., Teo, M., 2009. Institutional investors, past performance, and dynamic loss aversion. Journal of Financial and Quantitative Analysis, 44(1), 155–188.

Osborne, M.F., 1962. Periodic structure in the Brownian motion of stock prices. Operations Research, 10(3), 345-379.

Pierdzioch, C., Rülke, J.C., Stadtmann, G., 2013. Forecasting metal prices: Do forecasters herd?. Journal of Banking & Finance, 37(1), 150-158.

Romano, J.P., Shaikh, A.M., Wolf, M., 2010. Hypothesis testing in econometrics. Annual Review of Economics, 2(1), 75-104.

Sonnemans, J., 2006. Price clustering and natural resistance points in the Dutch stock market: a natural experiment. European Economic Review, 50(8), 1937-1950.

Sullivan, R., Timmermann, A., White, H., 2001. Dangers of data mining: the case of calendar effects in stock returns. Journal of Econometrics, 105(1), 249-286.

Tang, K., Zhu, H., (2014). Commodities as Collateral. Working Paper (August 22, 2014), SSRN: http://ssrn.com/abstract=2355674

Todorova, N., Worthington, A., Souček, M., 2014. Realized volatility spillovers in the non-ferrous metal futures market. Resources Policy, 39, 21-31.

Tokic, T., 2011. Rational destabilizing speculation, positive feedback trading, and the oil bubble of 2008. Energy Policy, 39(4), 2051-2061.

Watkins, C., McAleer, M., 2004. Econometric modelling of non-ferrous metal prices. Journal of Economic Surveys, 18(5), 651-701.

Watkins, C., McAleer, M., 2006. Pricing of non-ferrous metals futures on the London Metal Exchange. Applied Financial Economics, 16(12), 853-880.

Institute for International Integration Studies
The Sutherland Centre, Trinity College Dublin, Dublin 2, Ireland