Global Economy and Finance Journal
Vol. 4. No. 2. September 2011. Pp. 1-12

Psychological Barriers and Prices Behaviour of TAIFEX Futures

Ming-Hsien Chen* and Vivian W. Tai**

This paper investigates whether psychological barriers exist in a variety of daily TAIFEX futures price series. We use a number of statistical procedures and present evidence of psychological barriers in prices. Our results show that prices in round numbers act as barriers with important effects on the conditional mean and variance of the futures price series around these psychological barriers.

JEL Classification: D03, G14

1. Introduction

In practice, investment reports, suggested by security analysts, commercial research groups, financial correspondents and others, usually appear to investors when the index has risen or fallen below a certain level. Those recommendations usually predict up or down trends of the index when the index reaches or is near a specific level. In addition, those recommendations postulate specific index levels as reference points (price barriers), and encourage investors to trade when the index has touched or passed those levels. Those price barriers, which could be psychological barriers in terms of the behavioral aspect, could increase the impact of price changes when the price index is near or passes those specific levels, especially when those levels involve round numbers.

In this paper, we examine the existence of psychological price barriers which could arise from those specific index levels found in the abovementioned recommendations, especially when those levels involve round numbers. The effect of psychological barriers can be explained by an anchoring effect, and usually rely on a reference point in the past as a benchmark according to new information received. Kahneman and Tversky (1981) pointed out that when people make a decision under uncertainty, individual characteristics play a very important role. Consistent with the existence of limited arbitrage (Shleifer and Vishny, 1997) and psychological aspects of human information processing and decision-making, a number of behavioral biases have been shown to persist in asset price series (Hirshleifer, 2001). For example, the concepts of anchoring and heuristic simplification in behavioral finance are closely related to the issue of psychological barriers. Anchoring (Slovic and Lichtenstein, 1971) is the phenomenon whereby individuals fixate on a recent number or a number which may be held out to be important by informed commentators. Drawing on the heuristics concept of Kahneman, Slovic, and Tversky (1982) and on herding behavior of Avery and Zemsky (1998) and Welch (2000), Westerhoff (2003) develops formal

*The Authors thank all participants' valuable suggestions at the APBR conference in February 2011.
Ming-Hsien Chen,Assistant Professor, Department of Finance, National Kaohsiung First University of Science and Technology, Taiwan, Adds: No. 2, Jhuoyue, Rd., Nanzih District, Kaohsiung City 811, Taiwan, E-mail: morris.mhchen@gmail.com, Tel: +886-7-6011000 ext. 4017, Fax: +886-7-6011041.
** Corresponding Author, Assistant Professor, Department of Banking and Finance, National Chi Nan University, Taiwan, Adds: No.1 University Rd., Puli, Nantou 545, Taiwan, E-mail: whtai@ncnu.edu.tw, Tel: +886-49-2910960 ext. 4636, Fax: +886-49-2914511.

models of how traders cluster expectations around round numbers. Other researchers (e.g., Sonnemans, 2003) note a number of issues relating to competing hypotheses around why these barriers might a priori be expected, and suggest that in addition to the anchoring approach, an element of the phenomenon of odd-ending pricing[1] may be important.

Shiller (2000) notes that many traders focus on the nearest round number as a reasonable proxy for the fundamental value, in the absence of accurate fundamental analysis. In terms of limited memory, Stiving and Winer (1997) reveal that given a few figures, such as: 4869, most people may only remember the round number, 48. From left to right comparison, the result of digital encoding is from left to right and most people often ignore the next part of the memory mantissa and thus direct comparison of the first two numbers. For example, (21, 15) and (18, 12) are two groups of numbers and are not the same. However the essence of the difference between the two groups is 6.

Olsen (1998) points out that among the many diagnostic tools, most investors would utilize the integer points in the financial news or securities analysts comments on the most frequently mentioned integer points in a particular market index, for example, 7500 or 8000 points. Thus, reference points residing in such information affect investor psychology as a index rises or falls, especially when the index falls below a particular psychological level. Ley and Varian (1994) use the Dow Jones industrial average index from 1952 to 1993 to test whether the phenomenon of psychological barriers exist. They conclude that no evidence of a significant psychological barrier exists. Westerhoff (2003) examines the behavior of exchange rate fluctuations in terms of anchoring effects and psychological barriers. They find that traders actively trade between the exchange rate anchors. In addition, Aggarwal and Lucey (2007) show prices in round numbers act as barriers with important effects on the conditional mean and variance of the gold price series around psychological barriers. Other researchers (Mitchell and Izan, 2006; Mitchell, 2001) draw a distinction between psychological barriers and clustering phenomena to distinguish clustering (when particular digits and levels appear more often) from psychological barriers (which represent frequent trades at or around a particular cluster of prices). They find that these two aspects are related but not synonymous. Clustering is a necessary, but not a sufficient condition, for a psychological barrier to be present. Tschoegl (1988) shows that while all psychological barriers can be assumed to be round numbers, it is not the case that all round numbers are psychological barriers.

The extant literature suggests that the phenomenon of psychological barriers in financial markets does exist. Tschoegl (1988) points out that all of the psychological barriers are assumed to be formed in integers, but not all integers have a psychological barrier phenomenon. Psychological barriers can be explained by the arching effects, which define the phenomenon of those who are unfamiliar with or unsure of the situation feeling fear. Amir and Ganzach (1998) study the amendment of earnings forecast from analysts and find the existence of an anchoring effect, since the adjustment in analyst earnings forecasts is around the previously revealed values. McElroy and Dowd (2007) observe characteristics of openness-to-experience, (when individuals tend to make adjustments when accepting new information) and find that the anchoring effect is positively related to the openness-to-experience. In addition, Bharati, Crain and Kaminski (2008) show daily prices in crude oil futures are examined for evidence of clustering in the least significant integer digit and strongly indicate clustering in digit values around 9 coinciding with periods of OPEC credibility. Aggarqal and Lucey (2007) points out that the concept of anchoring effect is closely related with the psychological barrier.

We use a number of statistical procedures to assess psychological barriers for three nearest futures contracts, covering recent periods of one decade. The paper documents for the first time that there indeed are significant changes in means and variances associated with certain round number futures prices that are perceived as psychological barriers. Given the importance of futures, these results should be of much interest to policy-makers, scholars, and investors. Our results contribute to the literature by linking psychological barriers with the anchoring effect and, moreover, we provide evidence of prospect theory, proposed by Kahneman and Tverskey (1979), by identifying price behavior around the barrier from a downwards and upwards direction.

This paper is structured as follows. The next section shows the sample and related statistics, followed by a section on outlining strategies for testing psychological barriers. Section 4 describes the results from a variety of tests and section 5 concludes.

2. Sample Descriptions

We use the daily closing prices of three nearest futures contracts of Index Futures (TX), Finance Sector Index Futures (TF) and Electronic Sector Futures (TE) in our sample. The sample period is from January 4, 2000 to December 31, 2009, including 2,504 samples from the Taiwan Economic Journal (TEJ).

Table 1: Descriptive Statistics of TX, TF and TE Futures

Panel A. Price Level

	Mean	Median	Max.	Min.	Std. Dev.	Skewness	Kurtosis	Jarque-Bera value	Observations
TX	6416.52	6130.5	10352	3427	1467.73	0.4613	2.5134	113.4968	2504
TF	853.34	885.4	1256	434.8	163.97	-0.2578	2.4035	64.8495	2504
TE	281.28	268.5	573	142.6	76.14	1.1625	4.5075	801.0555	2504

Panel B. Returns statistics

	Mean	Median	Max.	Min.	Std. Dev.	Skewness	Kurtosis	Jarque-Bera value	Observations
TX	-1.71E-05	0.0004	0.0689	-0.0878	0.0188	-0.1997	5.6627	756.3723	2504
TF	-3.04E-05	0.0004	0.0727	-0.0995	0.0216	-0.1649	5.1702	502.7257	2504
TE	-0.0001	0.0004	0.0682	-0.0952	0.0219	-0.1172	5.0065	425.8021	2504

Sample period is from 4, Jan. 2000 to 31, Dec. 2009. We use log-return, $R_t = \ln(P_t / P_{t-1})$, in the study, thus, return could violates the 7%, in term of arithmetic measurement.

Panel 1 in Table 1 shows the descriptive statistics on TX, TE and TF futures. Statistical characteristics of samples are similar. The mean of TX (TF, TE) is about 6,416.52 (853.34, 281.28) with a standard deviation, 1,467.73 (163.97, 76.14) and only TX is above the thousand points. Furthermore, the distributions for TX and TE futures contracts are skewness-to the-right, whenever TF is left-skewed which shows the trend of TF is over its average, while TX and TE are mostly volatile below the average. Kurtosis of the three futures series shows they are differently distributed which is also supported by Jarque-Bera statistics. TX and TF exhibit a low broad peak pattern (platy kurtosis), but TE has high kurtosis (lepto kurtosis). Panel 2 shows the descriptive statistics on TX, TE and TF futures' return process. On average, the mean of daily returns in all three futures are negative, where TF has the largest negative value, while TE compensates the smallest negative premium. The skewness of the three futures is negative; indicating they are left-skewed which means that the trend of TF, TX and TE is respectively over its average. In the kurtosis, all coefficients are greater than 3, implying a high kurtosis distribution which can be supported by the Jarque-Bera statistics in the 1% significance level. Roughly, the returns on the three futures do not seem to follow a normal distribution of daily returns.

3. Methodology

We firstly investigate whether there is an abnormal movement of futures at a hundred and thousand points of the prices. Then we study whether the first and second moments of the futures prices are significantly different from those far from the 100 or 1000 integer points. In short, this section focus on the following issues, (a) setting methodology and type of integer points, (b) the meaning of M value and its measurement, (c) test on the existence of integer points, and (d) the effects of barriers on returns and volatility of futures prices.

3.1 Setting Methodology and Type of Integer Points

The range of an index depends on the number of listed companies, and the market capitalization of components. It therefore results in different types of futures targeted on three index levels. On the TWSE and TAIEX indexes, they are around thousand points, but the range of the electronic index are hundreds points. The financial insurance index and FX shows some breaks of thousand points, but the index of these thousand points are fewer relative to the total sample. Therefore, in our research, the empirical designs are different for three index futures for their distinct index ranges; the psychological barrier of FX is examined by hundred and thousand barrier points while TF and TE are examined only by hundred barrier points.

We follow the methods adopted by Burke (2001) and Donaldson and Kim (1993) to set the barrier points of 100 and 1000, applying to two psychological impacts on investors. One is the strict checkpoints and the other is the region level.

(1) Strict barrier

a. Distance between points in the hundreds of checkpoints, the setting methods, such as,

$$K \times 100, \quad K = 1, 2, 3, \ldots \qquad (1)$$

For example, 100, 200, …, 6100, 6200….

b. Point spacing of thousands of points, the set is shown as,

$$K \times 1000, \quad K = 1, 2, 3, \ldots \qquad (2)$$

For example, 3000, 4000, 5000, …

(2) Region level

We set the region levels to plus or minus 00 points for index points, for example: 95-05 or 90-10 as a hundred barrier. Different from strict checkpoints setting, region level allows us to find whether investors beforehand reflect their behavior on the futures prices near around the “00” or “000” checkpoints.

3.2 M Values and Measurements

M is two digital numbers, ranging from “00” to “99”, and usually represents a point, “00” as an important reference point. When investors have psychological barriers, the M value appears abnormal in the vicinity of “00”. The settings of M values are defined as follows[2].

(1) Hundred, “00”, barrier points of the M value is set as,

$$M^a = [P_t] \text{ mod } 100, \tag{3}$$

where $[P_t]$ is the integer part of P_t, [mod 100] is the two digital integers. For examples, if the prices are 159.36 and 3568.62 , M^a are 59 and 68, respectively.

(2) Thousand, “000”, barrier points of the M value is set as,

$$M^b = \left[100 \times 10^{(\log p_t) \text{ mod } 1}\right] \text{ mod } 100, \tag{4}$$

where M^b is the second and third digit of the price in terms of thousand measure and logarithms are to base 10. For example, if the prices are 9654.32 and 7896.99, M^b are 65 and 89, respectively.

For an examination of barriers, we are interested in whether the pair of digits bracketing the decimal point displays a frequency that is different from other pairs of digits. If there exist barriers at levels such as these, then we would expect to see relatively fewer x00.xx digits for “00”, and x00x.xx digits for “000” barrier points than otherwise. The term “mod” refers to the reduction modulo. These are known formally as M-values. Such frequencies would also depend on the execution of stop and limit orders and could well determine different dynamics approaching the barrier from below or from above.

3.3 Methodology of Identifying Price Barrier Points

The third issue of the paper is to investigate whether the abnormal distribution of futures prices exist when the prices are near the barrier points. We follow the approach adopted by Aggarwal and Lucey (2007) and Burke (2001) to examine the index clusters in order to identify whether an abnormal distribution is present. The M value of the cumulative number of points will be compared with non-integer values. We use the calculated M values coupled with the points test to find out whether the index level has an impact on investor psychology. Regression models contain two kinds of test points, the first test is called the value of the cumulative number of test points M (barrier proximity), and the other test is the barrier kurtosis test (barrier hump). Regression models are as follows,

(1) M value of the cumulative number of test points (barrier proximity),

$$f(M) = \alpha + \beta D + \eta \qquad \mathrm{M} = 00, 01, ..., 99, \tag{5}$$

$f(M)$ refers to the cumulative frequency of M values, *D* is a dummy variable.

When the prices reach on the strict barrier or near the region barrier, *D* is 1, otherwise *D* is 0. η is the residual term.

Barrier setting in the study is constructed as,

strict barrier: M = 00,

region barrier: (1) M > 95, or M< 05,

(2) M > 90, or M< 10.

Donaldson and Kim (1993) find that the M values at “00” of U.S. Dow Jones Industrial Average (DJIA), the cumulative numbers are lower relative to other M values, but Bahng (2003) shows M values at “00” of Indonesia's Jakarta Composite Index are higher than non-barrier price regions. In this paper, we assume that β is 0, when there is no price barrier effect, otherwise β may have significant negative or positive values.

(2) Barrier hump testing,

$$f(M) = \alpha + \varphi M + \gamma M^2 + \varepsilon \qquad \mathrm{M} = 00, 01, ..., 99, \tag{6}$$

where f (M) is the cumulative frequency of M values and ε is the residual term. In equation (6), we are concerned with the kurtosis distribution of M values and therefore we test whether there are unusual barrier hump effects. If the effect does not exist, the M value should be a uniform distribution (γ is zero); on the other hand, if the effect exists, the distribution of the M value is not uniform and γ is significantly different from zero.

3.4 Effects of Barriers on Returns and Volatility of Futures Prices.

The barrier, default reference price, is generally regarded as a resistance or a support price level in terms of investor’s psychology. In this subsection, we use a GARCH (p, q) model to investigate the effects of a barrier to returns and volatility on futures prices. The model is as follows,

$$Y_t = X_t b + \varepsilon_t, \quad \varepsilon_t \mid \Omega_{t-1} \sim N(0, \sigma_t^2) \tag{7}$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2 \tag{8}$$

In order to observe the behavior of index returns on or near the barrier, we define four dummy regimes around barriers: BU is 1 when the futures price 5 days prior to reaching a barrier is lower than the futures price on the day of reaching a barrier , AU is 1 when the futures price on the 5th day after reaching the barrier is above the futures price on the day of reaching a barrier, and BD and AD are 1 when the futures price 5 days before and after reaching the barrier moves in a downward direction. Bollerslev and Wright (2001) point out that the GARCH (1,1) model can successfully estimate and predict better than other more complex or conditional variance ones. Therefore, we use GARCH (1,1) model to observe the behavior of index returns on or near the barrier.

$$R_t = \beta_1 + \beta_2 BD_t + \beta_3 AD_t + \beta_4 BU_t + \beta_5 AU_t + \varepsilon_t, \quad \varepsilon_t \sim N(0, h_t), \tag{9}$$

$$h_t = \alpha_1 + \alpha_2 BD_t + \alpha_3 AD_t + \alpha_4 BU_t + \alpha_5 AU_t + \alpha_6 h_{t-1} + \alpha_7 \varepsilon_{t-1}^2 + \eta_t, \tag{10}$$

where $R_t = \ln(P_t / P_{t-1})$, represent the log-return of futures prices. BD_t, AD_t, BU_t and AU_t take the value 1 for the days noted, and zero otherwise.

4. Empirical Results

Results for the barrier proximity for the M value of hundred “00” and thousand “000” are shown in Table 2. It is clear that we can reject the no strict barriers hypothesis for the 100’s digits in TX series, but not for the 1000’s digits. Barriers in the daily TX series appear from this test to exist at levels such as 4100, 5100 etc but not at levels such as 4000, 5000 etc. Barriers in TF and TE, however, do not seem to exist (as strict or region barriers). There is some evidence of barriers at all forms of specifications (strict and region). Thus we concentrate on the strict test formulation of barriers. Points in the integer digits of a hundred points are studied on all futures. In the case of strict barriers, the coefficient of TF is negative, indicating TF futures have lower frequency on or around hundreds barriers and TX on or around thousands barriers.

Table 3 shows the results of the barrier hump test but there is little evidence here of a persistent barrier. The test of this part is mainly to study whether there is an abnormal level distribution in the frequency distribution of M values of kurtosis. The value of the peak from the M is observed in the vicinity of barriers. In hundred barriers, the coefficient of TE is positive indicating higher frequency on or around the barriers. TF has significantly negative coefficient in hundreds barriers, a similar result to the barrier proximity test. As for the TX, empirical results show TX has no barrier effects no matter in hundreds or in thousands points which contradict the results of the strict barrier test shown in Table 2. For the sake of robustness, we need more accurate evidence in the form of a GARCH model test.

Psychological barriers are generally taken as offering “support” or “resistance” to a series. The statistical interpretation of this is that the dynamics of the returns series around and in the vicinity of these barriers should differ from that elsewhere. We do not impose exogenous assumptions regarding the impact of being in the barrier region. Instead, what is of interest is the issue of the differential effect on the return and volatility from being in the region of the barrier, and whether the barrier is being approached from above (towards a hypothesized support barrier) or below (towards a presumed resistance barrier). The results are shown in Table 4, which uses a GARCH (1,1) analysis of the returns shown in equations (9) and (10). Again, we expect that in the absence of barriers the coefficients on the indicator variables in the mean equation would be insignificantly different from zero.

In the mean equation, the coefficients of AD are all significantly negative in TX, TF and TE, which shows that while prices pass down through the support, the attitude of investors changes from risk averse to risk loving as prospect theory postulates. Thus, investors are reluctant to realize their losses and hence, prices keep falling. Conversely, the coefficients of AU are all significantly negative which shows that when prices pass resistance levels, the attitude of investors shifts from risk loving to risk averse as prospect theory postulates. Consequently, investors intend to realize their positions as soon as possible to avoid regret when prices reverse in the future and, at the same time, the price rising movement is impeded and returns become negative. Additionally, the absolute values of AD and AU are all larger than BD and AD, which suggests that investors mainly trade after price barriers are passed. This result provides proof of the importance of reference points in investment mentioned in the prospect theory by Kahneman and Tverskey (1979).

Meanwhile, there are clear, consistent, and strong indicators of significant variance effects around barriers. The coefficients of BD and BU are significantly positive, which shows investor opinions are divergent before reaching a support or resistance level and hence, market movements are more volatile. Afterwards, the coefficients of AD and AU become significantly negative, which shows investor beliefs become consistent and the market calms down after passing through a support or resistance level. That is why we see that market volatility decreases. For futures returns, it is generally accepted that volatility is greater in bear conditions (see Campbell & Hentschel, 1992) and that leverage effects exist.

Table 2: Barrier proximity test

Panel A. Hundred points

	strict barrier		95-05 Region Barrier		90-10 Region Barrier	
	β	P-value	β	P-value	β	P-value
TX	0.0134***	0.0072	-0.0003	0.8684	-0.0001	0.9341
TF	-0.0012	0.5619	-0.0010	0.1532	-0.0009*	0.0756
TE	0.0004	0.8767	0.0001	0.8548	-0.0010*	0.0963

Panel B. Thousand points

	strict barrier		95-05 Region Barrier		90-10 Region Barrier	
	β	p-value	β	p-value	β	p-value
TX	-0.0004	0.8547	0.0007	0.3242	-0.0001	0.9028

The table shows the results of a regression, $f(M)=\alpha+\beta D+\eta$, where the dependent variable is the frequency of appearance of individual modulo values and D is a dummy variable that takes the value 1 in the presence of a barrier. Strict barrier takes the value 1 at the zero modulo point, 95-05 barrier takes the value 1 if the modulo is in the 95-05 interval, and 90-10 barrier takes the value 1 if the modulo is in the 95-05 interval. The data in the 100's digits column examine barrier behavior at the level of hundreds, that in 1000's digits that at the level of thousands. *p*-value gives the marginal significance of the coefficients against a null of zero.

Table 3: Barrier hump test

	Hundred points		Thousand points	
	γ	p-value	γ	p-value
TX	-3.390E-07	0.6177	4.140E-07	0.1524
TF	-5.510E-07**	0.0473		
TE	1.790E-07	0.5905		

The table shows the results of a regression, $f(M) = \alpha + \varphi M + \gamma M^2 + \varepsilon$, where the dependent variable is the frequency of appearance of individual modulo values and *M* is the frequency of appearance of individual modulo values. *p*-value gives the marginal significance of the coefficients against a null of zero.

Table 4: GARCH analysis: Barrier in hundred points for futures price series

	TX		TF		TE	
	Coefficients	p-value	Coefficients	p-value	Coefficients	p-value
Panel A: mean equation						
β_1	0.0008	0.4640	0.0002	0.5623	0.0007**	0.0651
β_2 (BD)	-0.0006	0.3247	-0.0031***	0.0017	-0.0003	0.8642
β_3 (AD)	-0.0051***	0.0000	-0.0115***	0.0000	-0.0100***	0.0000
β_4 (BU)	0.0019	0.1444	0.0037***	0.0001	0.0037***	0.0104
β_5 (AU)	-0.0055***	0.0000	-0.0099***	0.0000	-0.006***	0.0002
Panel B: conditional volatility equation						
α_1	-4.29E-06	0.1212	2.30E-06***	0.0068	4.38E-06***	0.0000
α_2 (BD)	1.35E-05***	0.0000	2.47E-05***	0.0000	2.70E-05**	0.0247
α_3 (AD)	-4.22E-06	0.1675	-5.07E-07	0.9385	-1.22E-05	0.2513
α_4 (BU)	1.03E-05***	0.0006	2.12E-05***	0.0001	1.47E-05*	0.0779
α_5 (AU)	7.85E-06**	0.0330	-5.71E-06	0.3184	-9.85E-06	0.1399
α_6	0.9026***	0.0000	0.8798***	0.0000	0.9119***	0.0000
α_7	0.0814***	0.0000	0.0925***	0.0000	0.0749***	0.0000

Table shows the results of a GARCH estimation of the form, $R_t = \beta_1 + \beta_2 BD_t + \beta_3 AD_t + \beta_4 BU_t + \beta_5 AU_t + \varepsilon_t$; $\varepsilon_t \sim N(0, h_t)$; $h_t = \alpha_1 + \alpha_2 BD_t + \alpha_3 AD_t + \alpha_4 BU_t + \alpha_5 AU_t + \alpha_6 h_{t-1} + \alpha_7 \varepsilon_{t-1}^2 + \eta_t$. AU, BU, AD and BD are dummy variables. BD and AD for the 5 days before and after breaching the barrier in a downwards direction; BU is for the 5 days prior to the gold price reaching a barrier from below, but before it reaches the barrier, and AU for the 5 days after the barrier from below,. Thus these take the value 1 for the days noted, and zero otherwise. *p*-value gives the marginal significance of the coefficients against a null of zero.

5. Conclusion

This article attempts to investigate the round numbers effect, the psychological impact on investors, and the behavior of futures prices near or on the barrier points. The effects of psychological barriers can be explained by an anchoring effect. Investors may rely on reference points in the past as benchmarks when new information is received to reduce the uncertainty. Prior research documents a psychological barrier as a support or resistance level, and stresses the importance of round numbers in equity, bond, foreign exchange and gold markets. Despite the importance of psychological elements in security markets, there is no prior research on these phenomena in the TAIFEX futures market. Using a number of statistical procedures, this paper examines, for the first time, mean and volatility effects around psychological barriers in Taiwan's futures market.

Moreover, in terms of frequency and time series tests, we find that the TX futures price series has strict barriers in hundred points but not in thousand points. TF and TE contracts have small negative coefficients in hundreds region barriers. Our results support Barber and Odean's (1999) viewpoint that decision making on investment may arise from cognitive biases (perhaps formed from past experience) in that different investors may have different psychological barriers. Therefore some futures price series exhibit round number effects in psychological barriers, but some do not.

Finally, the results of mean equations in the GARCH analysis are consistent with the prospect theory. When the futures prices fall below the presupposed round points, the investors suffer losses for their risk loving attitudes; otherwise, when the futures prices rise above the presupposed round points, the investors intend to realize their gains as soon as possible to avoid regret. The volatility indicator after passing through a barrier is in all cases negative, indicating that the market has calmed down. Consistent with this is the fact that in all cases, the indictor before a downward movement is positive, indicating investor beliefs are inconsistent and therefore markets are more volatile.

Endnotes

1. The phenomenon of odd-ending pricing is the price of ending the set, such as: $ 199 or $ 200 to explore ways to increase sales, the so-called "psychological pricing" (Mason and Mayer, 1990). A fractional pricing strategy tries to change consumers' perception in prices. Schindler (1991) and Stiving and Winer (1997) view the price effect both as an image and a level, when an integer for the mantissa, on behalf of better quality, is used by investors. Limited memory capacity, from left to right comparison, and a barrier close to an integer (round price down) and other three strategies are the most commonly discussed. Thomas and Morwitz (2005) study ending 9 pricing strategies and find that when a price change is in the far left of the target price, prices ending in a 9 have significant impact on the price perception.

2. See De Ceuster et al. (1998) for more details.

References

Aggarwal, R and Lucey,BM 2007, 'Psychological Barriers in Gold Prices?', *Review of Financial Economics, Vol. 16, No. 2, pp.217-230*.

Amir, E and Ganzach, Y 1998, 'Overreaction and Underreaction inAnalysts' Forecasts', *Journal of Economic Behavior and Organization, Vol. 37, No. 3, pp.333-347.*

Avery, C and Zemsky, P 1998, 'Multidimensional Uncertainty and Herd Behavior in Financial Markets', *American Economic Review, Vol. 88, No. 4, pp.724-748.*

Bahng, B 2003, ‘Do Psychological Barriers Exist in the Stock Price Indices? Evidence from Asia’s Emerging Markets’, *International Area Review, Vol.6, No. 1, pp.35-52*.

Barber, BM and OdeanT 1999, ‘The Courage of Misguided Convictions’, *Financial Analysts Journal, Vol.55, No.6, pp.41-55.*

Bharati, R Crain, SJand Kaminsky,V 2008, ‘OPEC Credibility and Clustering in Crude Oil Prices’, working paper, In: Proceedings of the 2009 FMA Annual Meeting, Reno-Lake Tahone, Nevada.

Bollerslev, T and Wright, JR 2001, ‘High-Frequency Data, Frequency Domain Inference, And Volatility Forecasting’, *Review of Economics and Statistics, Vol. 83, No.4, pp.596-602.*

Burke, S 2001, Barriers in US Benchmark Bonds, Working Paper, University of British, Columbia.

Campbell, JY, and Hentschel, L 1992, ‘No News is Good News: An Asymmetric Model of Changing Volatility in Stock Returns’, *Journal of Financial Economics, Vol. 31, No.3, pp.281-318.*

De Ceuster, MJK Dhaene, G and Schatteman,T 1998, ‘On the Hypothesis of Psychological Barriers in Stock Markets and Benford’s Law’, *Journal of Empirical Finance, Vol. 5, No.3, pp.263-279.*

Donaldson, RG and Kim, HY 1993, ‘Price Barriers in the Dow–Jones Industrial Average’, *Journal of Financial and Quantitative Analysis, Vol.28, No.3, pp.313-330.*

Hirshleifer, D 2001, ‘Investor Psychology and Asset Pricing’, *Journal of Finance, Vol.56, No.4, pp.1533-1597.*

Kahneman, D Slovic, P and Tversky, A 1982, *Judgment under Uncertainty: Heuristics and Biases*, Cambridge University Press, New York.

Kahneman, D and Tversky, A 1979, ‘Prospect Theory: An Analysis of Decision under Risk’, *Econometrica, Vol. 47, No.2, pp.263-292.*

Kahneman, D and Tversky, A 1981, ‘The Framing of Decisions and the Psychology of Choice’, *Science, Vol.111, No.3, pp.453-1131.*

Ley, E and Varian, H 1994, ‘Are There Psychological Barriers in the Dow–Jones Index?’,*Applied Financial Economics, Vol.4, No.3, pp.217-224.*

Lucey, B and Tully, E 2006, ‘Seasonality, Risk and Return in Daily COMEX Gold and Silver Data’, *Applied Financial Economics, Vol.16, No.3, pp.319-333.*

Mason, JB and Mayer, ML 1990, *Modern Retailing: Theory and Practice*, BPI /Irwin, Homewood, IL.

McElroy, T and Dowd, K 2007, ‘Action Orientation, Consistency and Feelings of Regret’, *Judgment and Decision Making, Vol. 2, No.6, pp.333-341.*

Mitchell, J 2001, ‘Clustering and Psychological Barriers: The importance of Numbers’, *Journal of Futures Markets, Vol. 21, No.5, pp.395-428.*

Mitchell, J., and Izan,IHY 2006, ‘Clustering and Psychological Barriers in Exchange Rates, *Journal of International Financial Markets*, *Institutions and Money, Vol.16, pp.318-344.*

Olsen, RA 1998, Behavioral Finance and its Implications for Stock-Price Volatility’, *Financial Analysts Journal, Vol. 54, No.2, pp.10-18.*

Schindler, RM 1991, ‘Symbolic Meanings of a Price Ending’, *Advances in Consumer Research, Vol.18, No.1, pp.794-801.*

Shiller, R 2000, *Irrational Exuberance*,Princeton University Press, Princeton.

Shleifer, A and Vishny,RW 1997, ‘The Limits of Arbitrage’, *Journal of Finance, Vol.52, No.1, pp.35-55.*

Slovic, P and Lichtenstein, S 1971, ‘Comparison of Bayesian and Regression Approaches to the Study of Information Processing in Judgment’, *Organizational Behavior and Human Performance, Vol. 6, No.1, pp.649-744.*

Sonnemans, J 2003,‘Price Clustering and Natural Resistance Points in the Dutch Stock Market’,working paper, Tinbergen Institute, Netherlands.

Stiving, M and Winer, R 1997, ‘An Empirical Analysis of Price Endings with Scanner Data’, *Journal of Consumer Research, Vol. 24, No.1, pp.57-67.*

Thomas, M and Morwitz, V 2005, ‘Penny Wise and Pound Foolish: The Left-Digit Effect in Price Cognition’, *Journal of Consumer Research, Vol.32, No.2, pp.54-64.*

Tschoegl, AE 1988, ‘The Source and Consequences of Stop Orders: A Conjecture’, *Managerial and Decision Economics, Vol. 9, No.4, pp.83-85.*

Welch, I 2000, ‘Herding Among Security Analysts’, *Journal of Financial Economics, Vol. 58, No.3, pp.369-396.*

Westerhoff, F 2003, ‘Anchoring and Psychological Barriers in Foreign Exchange Markets’, *Journal of Behavioral Finance, Vol. 4, No.2, pp.65-70.*