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PRICE EXHAUSTION AND NUMBER PREFERENCE: time and price confluence in Australian stock prices

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Abstract:

Confluence occurs when different trading filters generate signals that point to the same directional move. Using regression analysis, this paper investigates confluence trading signals associated with number preference and price exhaustion, for a sample of Australian stocks. The results show that certain price levels tend to act as psychological barriers, and that price exhaustion signals are a real phenomenon in the Australian stock market. It is shown also that confluence exists in the Australian stock market. Importantly, confluence is associated with price retracements that are of economic and statistical significance, offering profitable trading opportunities. The results suggest that Australian stocks do not follow a random walk.

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1. Introduction

Technical analysis is a set of extensively used techniques for identifying turning points in a stock market price series. These techniques focus on time, pattern, price, or a combination of all three (see Gilmore 1997 and Miner 1997). There are in fact a large number of technical analysis techniques, ranging from simple trend lines to more sophisticated price exhaustion signals.[2] The academic literature has focused on simple trading rules, such as the moving average crossover (see, for example, Gunasekarage and Power 2001). However, moving averages are only a minor component of a professional trader's set of tools. Unfortunately, advanced trading techniques have received very little attention from academic researchers.

The focus of this paper is on *confluence*. Confluence occurs when different trading techniques generate signals that point to the same directional move. The confluence signals explored in this paper are price signals associated with number preference and time signals associated with price exhaustion. Number preference arises when investors and traders assign greater weight to certain numbers, resulting often in the formation of psychological price barriers. Price exhaustion is a timing technique developed by DeMark (1994) to identify the termination of a price rally/decline. The existence of this type of confluence is explored by analyzing a sample of Australian stocks. Australian stocks have received very little attention from academic researchers, even though many are traded actively and many stocks, such as the National Australia Bank, Rio Tinto and News Corporation are recognized internationally and attract the interest of investors and traders from around the globe.

It is shown in this paper that confluence is a real phenomenon in the Australian stock market, and that it can be used to identify stock price movements that are of economic significance. Number preference is discussed in section 2 and DeMark's technique for detecting price exhaustion is discussed in section 3. Confluence of psychological barriers and price exhaustion is discussed in section 4. In section 5 regression analysis is used to show that confluence is associated with market reversals and that it influences the magnitude of a subsequent price swing. Some of the implications for trading and investing are presented in section 6.

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[1] This paper benefited significantly from comments made by anonymous referees, Darren Sheloff, Phillip Hone, Mehmet Ulubasoglu and seminar participants at the 3rd International Conference on Money, Investment and Risk.

[2] Excellent presentations on simple techniques can be found in Edwards and Magee (1992) and Guppy (1997). For more sophisticated techniques see Cowan (1993), DeMark (1994), Gilmore (1997) and Miner (1997).

2. Number Preference

Technical analysts argue that it is the forces of fear and greed that determine the wide swings observed in stock, commodity and currency prices (see, for example, Gately 1998 and Guppy 1997). Greed is said to drive prices upwards and fear is said to drive them down. This is especially evident during periods of buying frenzy and panic selling. While fundamental factors are important in determining the overall trend in a stock price, traders argue that the short and intermediate swings are driven mainly by psychological factors (see Gilmore 2002). Plummer (1993) points out that fear and greed can be stimulated by crowd behaviour, which can instil a large element of emotion, and at times irrationality, into investing and trading decisions.

This crowd psychology can lead also to price levels of psychological importance, where stock price rallies find resistance and where stock price declines find support. As Koedijk and Stork (1994) note: “Such levels appear not to be based on fundamental economic theory, but probably are created and kept alive by mass psychology” (p. 427). The business and finance media and probably most traders assign certain prices with psychological significance. Examples include 5,000 as a barrier for the NASDAQ and 10,000 as a barrier for the Dow Jones Index. Commencing with Osborne (1962), many researchers have produced empirical evidence of the existence of price clustering and psychological barriers. See, for example, De Grauwe and Decupere (1992), Koedijk and Stork (1994), Ley and Varian (1994), and Gwilym *et al.* (1998) among others. Aitken *et al.* (1996) present evidence of price clustering in the Australian stock market. Price clustering is the tendency of prices to deviate from a uniform distribution, tending to center around certain prices and avoiding others. Price clustering can be seen in many asset markets, such as prices of houses. Psychological barriers represent a more extreme form of clustering, as prices record a significant movement away from the barriers.

The psychological price levels literature has been challenged by De Ceuster *et al.* (1998) who argue that these price levels are consistent with a random walk process, and hence need not represent price barriers. De Ceuster *et al.* note that overrepresentation is a phenomenon of nature and is a natural part of number progression known as Benford’s (1938) Law of Anomalous Numbers, which has been observed in many random numbers, such as street addresses and areas of rivers. Regardless of the academic debate, the business finance press and most traders assign a behavioural aspect to these prices. They expect prices to be repelled from certain price levels and often these expectations are fulfilled.

In this paper, two sets of psychological price barriers are investigated. First, we follow previous researchers and consider integers, such as 100, 200, 300 etc, as potential psychological barriers. These are multiplicative regenerative, so that prices such as 1, 10 and 100 are considered also. The second set of psychological prices is the seemingly odd looking price series constructed by sequentially dividing 100 into two - $100, $50 (=100/2), $25 (=50/2), $12.50 (=25/2), $6.25 (=12.50/2), $3.125 (=6.25/2), $1.56 (=3.125/2), $0.78 (=1.56/2), etc.[3]

Numbers such as 1, 50 and 100 are obvious psychological price levels. For example, the number 100 is the basis of the metric system, and hence is of particular significance in the public's mind. Numbers such as $12.50 and $6.25 are *a priori* odd candidates for psychological price barriers and have not been explored previously by academics. However, it is shown in this paper that this number sequence does appear to be important, as least for the Australian stock market. Many traders use these numbers as part of their trading strategy. For example, this odd number sequence is part of the Murrey Math trading system, which is used in many markets, including forex and commodities (see Murrey 1995 for examples). There are other price series that have been noted in the trading literature. For example, Gann (1942, p. 19) notes that: "The average man thinks in multiples of 5 and 10. The popular trading prices are 25, 50, 60, 75, 100, 150, 175, etc." Gately (1998) highlights other price series used by the trading community, such as Fibonacci numbers (1, 3, 5, 8, 13, 21, 34, etc). Investigation of these and other series is beyond the scope of this paper.

There have been few theoretical studies on number preference, and this remains an important area for further research. It is not the intention of this paper to explore the origins of number preference, nor to identify the determinants of it. However, several explanations can be given for the presence of psychological price levels associated with integers. Harris (1991, p. 390), for example, argues that: "price clustering occurs because traders use a discrete set of prices to specify the terms of their trades". These discrete price sets lower the costs of negotiating and trading. Mitchell (2001) argues that price levels such as 100 derive their importance from habit and cultural factors.

Several reasons can be given for the existence of non-integer psychological price barriers, all of which are consistent with rational behaviour. First, there maybe a natural law of numbers, similar to Benford's law, that accounts for a non-integer number sequence. Authors such as Murrey (1995) state that this is the case, although they have not presented any rigorous discussion of the existence of such a law. Second, non-integer numbers may

[3] Note that these numbers are also multiplicative regenerative. Hence, we can derive also a sequence such as 0.625, 6.25, 62.50, 625.0, etc.

exist as barriers simply because enough traders use them as buy and sell points. That is, trading behaviour is revealed in market prices (see Ley and Varian 1994). For example, traders may have developed strategies for buying and selling stocks at prices which are derived from a simple strategy of dividing 100 by 2. Rather than using integers which the general public may use, traders may use levels that appear to be odd, such as $12.50, rather than say $13. This behaviour may have arisen out of custom and may even have become habit. Non-integers can arise also because of position size. Suppose a trader with a large position believes that $13.00 is as high as a stock will rise. There is no guarantee that they will be able to sell all of their position at $13.00, or even at $12.95, if the stock has relatively low liquidity. However, they may be able to dispose of most, or even all, of their holdings at a lower price, such as $12.50.

A third and more plausible explanation is the influence of broker recommendations. Investors and many amateur traders use broker recommendations as guidance and even take positions purely on these recommendations. Hence, broker recommendations can influence actual market stock prices. A full investigation of the impact of broker recommendations is beyond the scope of this paper, as it requires detailed analysis of broker recommendations over several decades. However, some tentative evidence is presented through a sample of broker recommendations for Australian stocks. These were derived from the Aegis database (purchased from Sanford Securities). Aegis is an independent Australian equities research house. The data used relates to the consensus of a panel of 20 advisory brokers (including brokers such as CS First Boston Australia, Deutsche Bank, JB Were, Macquarie Bank, Salomon Smith Barney and UBS Warburg). A random sample of broker consensus recommendations for 100 firms was taken, using the latest recommendations (which in most cases is November 2002).[4] Analysis of these broker recommendations is very revealing. For example, of the 100 stocks, 24 had broker recommendations for stocks ranging between $1 and $1.99. The mean and median broker consensus price target for this group of stocks was $1.50 and $1.54, respectively.[5] Of the 9 stocks trading between $2.00 and $3.00, the mean and median consensus recommendations were $2.45 and $2.40, respectively. These averages are very close to the numbers $1.56 and $2.50 which are part of the price series noted above. Table 1 compares the recommendations made in 2002 (column 3) to those made in 2001 (column 2), for a selection of these stocks. Table 1 indicates that numbers such as $1.56, $2.50, $3.13 and $6.25 are consistent with broker consensus recommendations. These

[4] This period falls outside the time period covered by the data used in the analysis in section 5. Hence, it should be considered as an out-of-sample exercise. The firms in the sample belong to different sectors, including energy, telecommunications, industrials, consumer, health care and telecommunications.

numbers act as areas of price resistance where prices stall, or as areas of price support, where prices bounce back upwards, at least temporarily and possibly for a substantial period of time. As a stock price rises and approaches the price recommended by brokers, buyers become less willing to purchase the stock at higher prices, and sellers become anxious to dispose of stock, as they believe that further capital gains are limited. Note that table 1 presents the averages of broker recommendations. Investors and traders may be influenced more heavily by one specific broker, rather than the average of all brokers, and this can lead to prices differing from the average of the recommendations, depending on the impact individual investors/traders have on recorded stock prices. Further research is needed to investigate the impact of individual broker recommendations and whether price stickiness is caused by broker recommendations, or whether broker recommendations are influenced by price stickiness.

TABLE 1 ABOUT HERE

3. Price Exhaustion

Many traders argue that there are cycles in stock markets that have a predictable pattern. In a series of books, DeMark (1994), (1997) and DeMark and DeMark (1999) have argued that stock prices exhibit a pattern of price exhaustion. DeMark hypothesizes that price exhaustion follows a pattern involving two main stages: the setup stage and the countdown stage. The entire process is known as the *sequential*. According to the research conducted by Demark, many stock price movements follow a pattern where they rally for a certain period of time and then typically retrace or move into a state of temporary congestion (they stagnate). DeMark calls this the setup stage. Stock prices then resume their uptrend for a certain period of time, before finally retracing again. This is known as the countdown stage. A similar process is said to occur for price declines. DeMark specifies the setup stage as a period involving 9 days and the countdown stage involving 13 days. DeMark established the numbers 9 (for the setup stage) and 13 (for the countdown stage) through an extensive analysis of historical data on commodities and stock prices and states that these time cycles work in a very wide range of financial markets. While other time frequencies are possible, such as an 8-day setup, in this paper we examine only the trading system specified by DeMark. No attempt is made to determine the optimal time frequency. Rather, the focus is on testing DeMark's model.

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[5] Anecdotal evidence from brokers indicates that there is a large element of herd mentality in their

Stage 1: The setup

DeMark defines a sell setup as a price rally/decline involving a series of 9 *sequential* days where the closing price is greater/lower than the closing price of 4 days earlier. The setup identifies a strongly trending stock. The 9 days must be sequential. If any day does not close higher than the closing price of 4 days earlier, then the setup process is cancelled, and traders look for a new setup to commence. [6]

Figure 1 illustrates the setup process, using daily stock price movements for Millers Retail (Australian Stock Exchange code MRL), showing a sequence of 9 days (numbered on the chart) where the close is greater than the close of 4 days.[7] In this example, the upswing terminated exactly on the 9th day of the setup, with the high of $6.39 for the swing coinciding with the high of day 9. This is not always the case. For example, the high for the swing may occur on day 7 or day 8, or after day 9. Notice the $6.25 price level marked on the chart. This is one of the numbers in the psychological price sequence identified earlier. Figure 1 illustrates one example of confluence, where a rally terminates when a price exhaustion signal develops near a psychological price level. Note that the sequential does not commence at the start of a rally. It commences the first day the closing price is higher than the close 4 days earlier.

FIGURE 1 HERE

Stage 2: The Countdown Stage

The countdown stage follows the setup stage and involves 13 days where the close is higher than the high of two days earlier for a rally (and where the close is lower than the low of two days earlier for a decline). The idea behind the countdown process is to identify the point at which a strongly trending stock experiences price exhaustion. Price exhaustion occurs when stock prices reverse direction. During the setup stage a stock rallies hard and then possibly retraces as many of those who have made a profit sell the stock in order to realize that profit. Strongly trending stocks will then continue to rally, possibly at a slower rate of growth. The countdown process tracks the resumption of the rally and, according to DeMark, it identifies the ultimate termination of the rally.

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recommendations. Devenow and Welch (1996) note that such imitation is a basic human instinct.

[6] There is a second intermediate stage that is sometimes used. This is known as intersection. See DeMark (1994) for details.

[7] Note that Figure 1 uses data prior to the bonus issue for MRL – the sequence is the same after the bonus issue, only the price levels differ.

The countdown process is illustrated in Figure 2, using data for Westpac Banking group (code WBC). The 9 day sell setup can be seen as the first series of numbers, numbered 1 to 9 (these must be sequential). This is followed by 13 days where the close is higher than the high two days earlier. These are numbered 1 to 13 (these need not be sequential). The 13th day of the countdown stage occurred near the peak of the swing. This peak fell close to the \$11.00 level, which is one of the integer psychological price levels. Note that the stock eventually found support around the \$10 psychological price level.

FIGURE 2 HERE

4. Confluence

A link between psychological barriers and price exhaustion presents itself as a combination of a stock price approaching a psychological price level while at the same time, the time component reaches a period where stock price advance/decline is expected to waver. Confluence is the simultaneous occurrence of price and time signals.

A third example of confluence is presented in Figure 3, illustrating price exhaustion in the form of a buy countdown coinciding with the \$1.56 price level, for Ecorp (code ECP). The numbers on top of the price bars trace the buy setup stage, while the numbers on the bottom trace the buy countdown stage. Both day 11 and day 13 of the countdown stage traded as low as \$1.58, forming what technical analysis call a 'double bottom'.[8] Price subsequently rose by 52 percent. Note that in this example, the buy setup stage involved a rapid decline in prices, while the countdown stage saw a more subdued reduction in prices.

FIGURE 3 HERE

The notion that price rallies or price collapses follow a predetermined pattern of time is inconsistent with the random walk hypothesis. The existence of confluence is at odds also with the hypothesis that stock prices follow a random walk. There have however been no published empirical investigations into these techniques.[9]

[8] This is regarded by traders as a powerful trading signal.

[9] The technique has been used by many traders, many of whom no doubt have undertaken their own research. Their research findings however are not available in the public domain. DeMark himself only offers chart examples, without any analysis of the incidence of price exhaustion.

5. Statistical Analysis of Confluence

In this section empirical evidence is presented showing that: (a) there is an association between market reversals and confluence signals; and (b) that there is an association between confluence signals and the magnitude of a stock price swing.

5.1 Data

The data used is based on a random sample of 20 Australian stocks. Australian stocks do not trade at price levels as high as those in other countries, such as the U.S. Hence, the analysis is restricted to those psychological price barriers which have been tested by the stocks. Only those stocks which have traded at least up to the $6.25 psychological barrier were considered. The data is daily and commences in November 1986 and ends at August 2001, giving a sufficient time span for the investigation.[10] In total there are 38,245 daily observations used in the analysis.[11] For several of the stocks the data do not commence in 1986, as the stocks were not listed on the exchange until after that date. The stocks span several industry sectors. The data was purchased from Almax Information Systems, and includes all of the publicly listed stocks on the Australian Stock Exchange, from which the sample was drawn.

5.2. Incidence of Confluence in Australian Stock Prices

The first task is to explore the incidence of confluence, defined as the coexistence of trading signals arising from both price exhaustion and number preference. We look for a signal where a stock price is rising (or falling), a price exhaustion signal is formed (either a setup or a countdown) and price comes within 5 percent of a psychological barrier.

The incidence of confluence *sell* signals is presented in table 2.[12] This lists the proportion of successful setups that were associated with the psychological price barriers discussed in section 2 above. Successful in this context means that a price retracement of at least 5 percent occurred once the price exhaustion signal was completed. A 5 percent retracement provides an opportunity for a profitable trade, after allowing for transaction costs.

Taking all the stocks together, approximately half of the successful sell setups and over 60 percent of the sell countdowns occurred with confluence. In both cases, the average price retracement is in excess of 10 percent, which can be considered to be of economic

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[10] The data used for the analysis is available from the author.

[11] The focus of this paper is on confluence in daily stock price movements. Confluence may arise in other time periods, such as weekly, monthly, as well as intraday (60 minutes etc). These are not investigated here.

[12] Confluence buy signals are not presented, but are broadly similar to the sells signals presented in Table 2. These are available from the author.

significance. For three of the stocks, all of the setups occurred with confluence. For 7 of the 20 stocks all of the countdowns occurred with confluence and for 5 of the stocks, none of the countdowns occurred with confluence. It should be noted that most of the swings in the stocks examined were not associated with psychological barriers, price exhaustion, nor confluence. That is, the majority of the stock price movements in Australian stocks do not coincide with these trading signals. The sample examined in this paper includes 1,931 stock price swings. Only 16 percent of these were associated with confluence signals. However, even though the confluence signals are a relatively rare event, when they do occur, there is a high probability of a price retracement. In particular, confluence that occurs with the full price exhaustion signal (proceeding from a setup to the termination of the countdown stage) has a higher probability of leading to a significant price retracement.

TABLE 2 HERE

Additional information can be derived by exploring the magnitude of the retracements associated with confluence. These are presented in table 3, according to the price level from which a retracement occurs. The majority of the price retracements are relatively large.

TABLE 3 HERE

5.3 Statistical Significance

Is confluence a real phenomenon or is it due merely to chance? To answer this question, we need to explore the link between market reversals and confluence signals. This can be delved into by estimating the following equation:

$$P_i = \alpha + \sum_{j=1}^{n} \beta_j D_j + \sum_{k=1}^{n} \gamma_k E_k + \sum_{j=1}^{n} \sum_{k=1}^{n} \delta_{jk} D_j E_k + \phi_1 P_{i,t-1} + \eta H + u_i \tag{1}$$

where P is the price (in dollars) at which a market reversal occurs at swing i, the D_j are dummies representing psychological price barriers, the E_k are dummies representing price exhaustion signals, $D_j E_k$ are interactive terms representing confluence (price exhaustion coinciding with psychological price barriers), $P_{i,t-1}$ is the lagged dependent variable, H

denotes the highlow variable which is a dummy taking the value of 1 if the price relates to a peak (swing high) and 0 if it relates to a trough (swing low), and *u* is a normal error term. The lagged dependent variable is included to capture autoregressive effects, while the highlow variable controls for market conditions. The D_j, E_k and $D_j E_k$ terms are included separately in order to isolate any individual effects. For example, it is possible that certain price levels act as psychological barriers but these may not be associated in anyway with price exhaustion signals. In such cases the $D_j E_k$ terms will have coefficients that are equal to zero.

The dependent variable was constructed as follows. First, all the market swings were identified for each stock. These are movements involving price rallies/declines of at least 5 percent. Second, the highest price for a rally and the lowest price for a decline were recorded. These are the values used for the P_i series. That is, the dependent variable is not the daily price, but it is either the highest price recorded in a rally or the lowest price recorded in a stock price collapse. This produces a total of 3,840 observations for the dependent variable. It is important to note that the D_j and E_k variables tested in this paper are not the result of a data mining exercise, that involves peaking at the data and using levels revealed in stock price histories. Rather, they are derived from what traders have stated publicly in the published technical analysis literature.

The estimation process was undertaken in two steps.[13] At the first stage, equation 1 was estimated including all the psychological price barriers, price exhaustion signals and confluence signals as explanatory variables, as well as the lagged dependent variable and the highlow variable. Not surprisingly, a number of the variables were statistically non-significant. Accordingly, at the second stage, these insignificant variables were removed sequentially, following the general-to-specific modelling strategy, until all remaining variables were significant at least at the 10 percent level. This process was repeated for each of the 20 stocks individually, as well as for all stocks combined. In the case of the later, individual stock dummy variables were included to control for stock specific effects. Each equation was tested for heteroscedasticity, ARCH effects and autocorrelation in the residuals. The regressions reported in this paper pass these diagnostic tests. Both OLS and Weighted Least Squares were used to estimate equation 1, for both the individual stocks as well as the pooled data. The results are virtually identical, and hence only the OLS results are presented here.

For the sake of brevity, only the results for the pooled dataset are presented. However, the results for the individual stocks are broadly similar to those presented for all stocks

[13] Eviews 4.0 was used for all the econometric analysis.

combined. The final specific results for the pooled dataset are presented in table 4. The results from the general model are also not presented. The full set of results is available from the authors.

The data is an unbalanced panel. Pooling this data is valid if homogeneity is assumed. Homogeneity is a plausible behavioural assumption for this group of stocks. Consider, for example, a system trader. These traders are looking for opportunities to short sell a stock once it meets resistance at a psychological barrier, once a price exhaustion signal is given, or preferably when both of these events occur. These traders are not following one stock. They follow groups of stocks. The stocks are treated as if they were identical. The trader's focus is on a pattern, searching for similar patterns throughout a pool of stocks. Since the analysis in this paper is on whether confluence is associated with market turns, then homogeneity is a logical assumption. Moreover, Baltagi *et al.* (2000) demonstrate that pooling is a preferable strategy. They show that the assumption of homogeneous parameters and the use of the OLS pooled estimator outperform heterogeneous models and estimators.

Of the potential psychological price barriers considered, the six price levels presented in Table 1 column 1, were the only ones that were statistically significant. These include both integer and non-integer numbers. Notice the importance of the \$1.56 and \$2.50 price levels, which are consistent with the consensus broker recommendations noted in section 2. Both the buy and sell setups are statistically significant, as are sell countdowns (see column 1). The remainder of the table presents the confluence signals. It is clear that many areas of confluence are statistically significant, confirming what is observed in stock price charts and the incidence presented in table 2. The most recurring price areas for confluence are the \$2.00, \$2.50 and \$3.00 areas.

TABLE 4 ABOUT HERE

The parameter estimates from equation 1 can be used to test a number of propositions. If $\sum \beta_i = 0$, none of the price dummies are statistically significant and hence there is no evidence of psychological price barriers. If $\sum \gamma_k = 0$, none of the price exhaustion variables are statistically significant and hence price exhaustion is not associated with market reversals. If confluence is associated with market reversals, then the D_jE_k interaction terms should be statistically significant. Hence, if $\sum \delta_{jk} = 0$, none of the confluence variables is statistically significant and we can conclude that confluence is of no importance. These tests were conducted as Wald Tests. The associated F-statistics are reported in table 4 (bottom of column

3). Each of these hypothesis is rejected.[14] The conclusion from table 2 is that prices recorded at market swing highs and lows are not random, rather they are associated with price exhaustion, psychological barriers and confluence signals.

Magnitude of Price Swings

Equation 1 can be used also to explore whether confluence is associated with differences in the magnitude of market reversals. In order to investigate this, equation 1 was reestimated, except that the dependent variable is now the *absolute* size of the swing expressed as a percentage. This was calculated by measuring the percentage change from the peak of a price swing to the subsequent trough (and from trough to peak). A general model was estimated first, and statistically insignificant variables were sequentially omitted. The final results are presented in table 5.

In the absence of price exhaustion, psychological price barriers and confluence, the average price swing is about 14 percent (the constant in table 5 is 13.99)[15]. Most of the coefficients in table 5 have a negative sign, which means that price swings are smaller when they are associated with these variables. There are, however, two notable exceptions. When buy setups coincide with the $1.56 psychological price barrier, price swings are about 28 percent larger. When the $1.56 psychological price barrier coincides with a buy countdown, the resulting price swings are about 37 percent higher. These price swings are large and are of economic significance. In both tables 4 and 5, the lagged dependent variable is significant which indicates autoregression. If the random walk hypothesis holds, autoregression should not be present in the percentage change equation.

TABLE 5 ABOUT HERE

From a traders perspective the issue is not whether a stock price swing is above or below a historical average. Rather, the issue is whether there is a higher probability that an emerging swing will be a profitable one. The whole basis of technical analysis is the use of rules and techniques designed to filter and highlight the more profitable and relatively low risk trading opportunities. In this paper, the association between stock market reversals and confluence signals have been shown to be both statistically significant and to be of economic significance, confirming that confluence is a useful filter.

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[14] Note that the lagged dependent variable has a coefficient of 0.98. A Wald test rejects the hypothesis that this is equal to 1.

[15] The actual average magnitude of price swings is 13.79 percent, which is very close to the estimated constant in the regression equation.

A final issue is whether the incidence of price exhaustion has decreased over time. Does knowledge of a technique based on an observable pattern make that pattern less widespread? If a profitable pattern is publicised, it may be expected that trading behaviour will eventually erode any profits associated with the use of such rules. To test this, the log of the number of price exhaustion signals per stock was regressed, for the period 1986 to 2001, against a constant, a time trend and a dummy variable for the publication of DeMark's first book in 1994. This variable takes a value of 0 prior to 1994 and a value of 1 thereafter.[16] The dummy variable for DeMark's book is not statistically significant. Publication of the book did not impact on the number of price exhaustion signals observed in the data. Interestingly, the coefficient on the time trend variable is 0.102, indicating an annual percentage rate of *growth* of around 10 percent. That is, instead of falling, the number of price exhaustion signals has been growing solidly over time. This contradicts also the random walk hypothesis.

6. Implications for trading and investing

It is customary in the academic literature to compare a trading signal to a buy-and-hold strategy. The results are not presented here, but it can be shown that for most of the stocks a buy-and-hold strategy generates a greater rate of return than trading the same stocks using confluence signals *alone*. This arises because most of the stocks (especially the banking stocks) in the sample have been in a long term rising trend. Since confluence signals are a relatively rare event, then they are not likely, on their own, to generate returns in excess of a buy-and-hold position for those stocks that are experiencing long-term trends. Trading on the basis of confluence signals alone does outperform in several cases, but these are all situations where the stock is either in a long-term decline or is in relative stagnation. It is pertinent to then ask what is the value of confluence.

Traders look for charting patterns and signals to aid their trading decisions and this usually involves considering information from more than one technique. To traders, confluence increases the probability that the signal will lead to a profitable trade. Whether the opportunities represented by the psychological levels and price exhaustion signals are realized by traders and investors depends on a number of factors such as a traders' risk profile, money management, entry and exit strategies, and the use of stop losses. More importantly, the profitability of trading depends also on the psychological make up of a trader. Most buy and

[16] The technique was known prior to 1994, but it was the publication of the book that increased the popularity of the technique.

hold investors choose not to trade because they don't have the skills to do so,[17] or the acquisition of such skills is seen as an expensive process, in terms of direct and importantly in terms of opportunity cost.

Confluence can be of use to traders. One viable strategy is for traders to exit their positions when a confluence sell signal is generated. That is, once they have entered a trade on the basis of some other indicator or trading strategy, they can use the confluence signal as an exit point. For example, in the event that a moving average crossover is used to initiate a trade, a position can be closed once a confluence signal arises. Traders may thus get a better exit than relying on a lagging indicator (such as a moving average) which would get them out at a lower price and hence lower rate of return.

Confluence can also assist buy and hold positions. Investors are entering buy and hold positions throughout a stocks' trading history, as new cohorts of investors enter the stock in their portfolio or additions are made to an existing portfolio. A confluence strategy would mean that buy and hold investors would not add positions/make new commitments until a retracement of say around 10 percent had occurred, after a confluence signal became manifest. This would mean that they could enter at a better price for new buy-and-hold positions.

Finally, confluence can also be of some assistance to policy makers. For example, confluence was present on both weekly and monthly charts on the Nasdaq index just as it was testing the 5000 barrier, in March 2000. These confluence signals indicate to policy makers that there is a greater probability of a retracement in a key stock price index, with the associated wealth effects and the associated flow-on effects on the real economy such as on employment. This knowledge may be of assistance, for example, to Central bankers in the formulation and execution of monetary policy. Similar patterns can be found in other assets,

[17] For example, traders often try to sell when most people are bullish and try to buy when most people are bearish – the so-called 'Buy in gloom and sell in boom strategy'. Such 'contrarian' strategies are taxing psychologically as they involve an individual taking a position that is opposite to the majority.

such as commodities and currencies. For example, in 2000 the Australian Reserve Bank tried in vain to stem a falling currency by manipulating interest rates. The Australian dollar finally found support around the 50 US cents area (a key psychological support level), together with confluence of price exhaustion on a weekly time frame. [18]

7. Summary

In this paper it was shown that certain price levels tend to act as psychological barriers in the Australian stock market. It was shown also that price exhaustion signals do arise in the Australian stock market and that many of these lead to significant price retracements. Price exhaustion signals can be combined with psychological barriers to generate confluence signals. It was shown that such confluence does exist in the Australian stock prices studied, and that they offer profitable opportunities. Confluence is a relatively rare phenomenon, but it is one that traders, investors and policy makers need to be aware of. Importantly, the existence of confluence indicates that Australian stocks do not follow a random walk.

The confluence explored in this paper is just one example of advanced trading techniques and strategies. These techniques are used by professional traders and warrant attention from researchers. In particular, other advanced techniques need to be explored and compared, and applied to stocks in different countries, as well as for different asset classes.

Several areas warrant further investigation. This includes examination of other potential psychological price levels, such as those emerging from the Fibonacci price series. The factors leading to psychological price barriers, as well as price exhaustion require also attention from researchers. Importantly, examination of stock markets in other countries is needed to identify whether confluence is a universal phenomenon rather than just an Australian one.

References:

Aitken, M., P. Brown, C. Buckland, H.Y. Izan and T. Walter, 1996, “Price Clustering on the Australian Stock Exchange”, *Pacific-Basin Finance Journal*, vol. 4, pp. 297-314.

Ball, C., W. Torous and A. Tschoegl, 1985, “The Degree of Price Resolution: the case of the gold market”, *The Journal of Futures Markets*, vol. 5, pp. 29-43.

Baltagi, B, J. Griffin and W. Xiong, 2000, “To Pool of not to Pool: homogenous versus heterogenous estimators applied to cigarette demand”, *The Review of Economics and Statistics*, vol. 82, pp. 117-26.

[18] The Australian dollar traded as low as 0.4785 US during the first week of April 2001. However, it closed at 0.499 that same week, finding support around the 0.50 psychological barrier and rallied from there. The first week of April came one week after a buy setup was completed.

Baltagi, B. 2001, *Econometric Analysis of Panel Data*, John Wiley and Sons, Chichester.

Benford, F, 1938, “The Law of Anomalous Numbers”, *Proceedings of the American Philosophical Society*, vol. 78, pp. 551-72.

Cowan, B, 1993, *Four-Dimensional Stock Market Structures and Cycles*, self-published.

Cowan, B. 1995, *Market Science, Vol. 1, Square of Twelve*, self-published.

De Ceuster, M.J.K., 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, September, p. 263-79.

De Grauwe, P. and D. Decupere, 1992, “Psychological Barriers in the Foreign Exchange Markets”, *Journal of International and Comparative Economics*, vol. 1, pp. 87-101.

DeMark, T. R., 1994, *The New Science of Technical Analysis*, John Wiley & Sons, New York.

DeMark, T. R., 1997, *New Market Timing Techniques: Innovative Studies in Market Rhythm & Price Exhaustion*, John Wiley & Sons, New York.

DeMark, T. R. and T. DeMark Jr, 1999, *DeMark on Day Trading Options*, McGraw Hill, New York.

Devenow, A. and I. Welch, 1996, “Rational Herding in Financial Economics”, *European Economic Review*, vol. 40, pp. 603-615.

Donaldson, G.R. and H.Y, Kim 1993, “Price Barriers in the Dow Jones Industrial Average”, *Journal of Financial and Quantitative Analysis*, vol. 28, pp. 313-30.

Downs, E., 1999, *The 7 Chart Patterns That Consistently Make Money*, Nirvana Systems.

Edwards, R. and J. Magee, 1992, *Technical Analysis of Stock Trends*, John Magee Inc. Boston, Massachusetts.

Fernandez-Rodriguez, F., C. Gonzalez-Martel and S Sosvilla-Rivero, 2000, “On the Profitability of technical trading rules based on artificial neural networks: Evidence from the Madrid stock market”, *Economics Letters*, vol. 69, pp. 89-94.

Gann, W.D. 1942. *How to Make Profits Trading in Commodities: a study of the commodity market*. Library of Gann Publishing Co, Pomeroy.

Gately, Ed. 1998. *Forecasting Profits Using Price and Time*. John Wiley and Sons, New York.

Gencay, R., 1998, “Optimization of technical trading strategies and the profitability in security markets”, *Economics Letters*, vol. 59, pp. 249-54.

Gencay, R., 1999, “Linear, non-linear and essential foreign exchange rate prediction with simple technical trading rules”, *Journal of International Economics*, vol. 47, pp. 91-107.

Gilmore, B., 1997, *Dynamic Time and Price Analysis of Market Trends: Advanced Technical Analysis Methods and Techniques*, Bryce Gilmore & Associates, Helensvale.

Gilmore, B., 2002, *Trading with an Edge*, Bryce Gilmore & Associates, Helensvale.

Gunasekarage, A. and D. M Power, 2001, “The Profitability of Moving Average Trading Rules in South Asian Stock Markets”, *Emerging Markets Review*, vol. 2, no. 1, pp. 17-33.

Guppy, D., 1997, *Trading Tactics*, Wrightbooks, Elsternwick.

Guppy, D. 1999, *Chart Trading*, Wrightbooks, Elsternwick.

Gwilym, O., A. Clare and S. Thomas, 1998, “Extreme Price Clustering in the London Equity Index Futures and Options Markets”, *Journal of Banking and Finance*, vol. 22, pp. 1193-1206.

Harris, L. 1991, “Stock Price Clustering and Discreteness”, *The Review of Financial Studies*, vol. 4, pp. 389-415.

Henriksson, R and R Merton, 1981, “On the Market Timing and Investment Performance II: Statistical procedures for evaluating forecasting skills”, *Journal of Business*, vol. 54, pp. 513-33.

Kho, B., 1996, “Time-varying risk premia, volatility, and technical trading rule profits: Evidence from foreign currency futures markets, *Journal of Financial Economics*, vol. 41, pp. 249-90.

Koedijk, K.G. and Stork, P.A, 1994, “Should We Care? Psychological Barriers in Stock Markets”, *Economics-Letters*, 44(4), April, p. 427-32.

LeBaron, B. 1999, “Technical Trading Rule Profitability and Foreign Exchange Intervention”, *Journal of International Economics*, vol. 49, pp. 125-43.

Ley, E. and H. Varian, 1994, “Are There Psychological Barriers in the Dow-Jones Index?”, *Applied Financial Economics*; 4(3), June, p. 217-24.

Martin, A. D., 2001, “Technical Trading Rules in the spot foreign exchange markets of developing countries”, *Journal of Multinational Financial Management*, vol. 11, pp. 59-68.

Mitchell, Jason, 2001, “Clustering and Psychological Barriers: The Importance of Numbers”, *The Journal of Futures Markets*, vol. 21, No. 5, pp. 395-428.

Miner, R., 1997, *Dynamic Trading: Dynamic Concepts in Time, Price and Pattern Analysis with Practical Strategies for Traders and Investors*, Dynamic Traders Group, Tucson, Arizona.

Murrey, T.H., 1995, *Murrey Math Trading System for all Traded Markets*, Green Hill Publishers, Nashville, Tennessee.

Osborne, M, 1962, “Periodic Structure in the Brownian Motion of Stock Prices”, *Operations Research*, vol. 10, pp. 345-379.

Pesaran, M and A Timmermann, 1992, “A simple nonparametric test of predictive performance”, *Journal of Business and Economic Statistics*, vol. 10, pp. 461-65.

Peters, Edgar E., 1994, *Fractal Market Analysis: Applying Chaos theory to Investment and Economics*, John Wiley, New York.

Plummer, Tony, 1993, *The Psychology of Technical Analysis*, Irwin, London.

Skouras, S., 2001, “Financial Returns and efficiency as seen by an artificial Technical Analyst”, *Journal of Economic Dynamics and Control*, vol. 25, pp. 213-44.

Tvede, Lars, 1990, *The Psychology of Finance*, Norwegian University Press,

Williams, Larry, 1999, *Long-Term Secrets to Short-Term Trading*, John Wiley, New York.

Table 1: Number Preference and Broker Recommendations

Stock	Consensus Recommendation	Latest Consensus Recommendation
ALL	$6.35 (29-10-01)*	$6.50 (24-10-02)*
AMP	$19.50 (5-10-01)	$13.00 (19-11-02)*
BEN	$5.54 (20-02-01)	$7.25 (19-02-02)
BSL	$3.35 (16-7-02)	$3.15 (19-11-02)*
FBU	$2.70 (10-9-01)*	$4.00 (14-11-02)*
HVN	$3.46 (20-11-01)	$3.15 (20-11-02)*
ION	$1.56 (28-9-01)*	$2.57 (31-10-02)*
MRL	$6.80 (30-9-01)	$3.28 (29-9-02)*
ORI	$6.25 (7-11-01)*	$12.50 (7-11-02)*
PPX	$4.25 (9-10-01)	$6.00 (24-10-02)*
TAH	$11.25 (20-9-01)*	$12.60 (25-10-02)*
UEL	$2.70 (2-09-01)*	$2.50 (14-09-02)*
WMC	$11.40 (30-11-01)	$10.00 (1-11-02)*
WYL	$2.00 (13-9-01)*	$3.05 (29-10-02)*

* price consistent with number preference.

Table 2: Incidence of confluence involving Setup Sell and Countdown Sell Confluence Signals

Stock	% of Successful Setups With Confluence	Average Price Retracement From Setup Confluence	% of Successful Countdowns With Confluence	Average Price Retracement From Countdown Confluence
AMP	17%	-10%	0%	0%
ANZ	48%	-17%	80%	-30%
BEN	40%	-10%	100%	-17%
CPU	25%	-20%	50%	-16%
ECP	75%	-12%	0	0
ETR	100%	-58%	100%	-60%
DAD	50%	-7%	50%	-16%
HAH	53%	-14%	86%	-9%
MRL	86%	-15%	0%	0%
NAB	44%	-11%	100%	-7%
RIO	47%	-16%	100%	-17%
SGB	43%	-12%	0%	0%
SME	38%	-18%	100%	-8
SNX	100%	-24%	100%	-26%
TAH	93%	-11%	50%	-18%
TLS	60%	-9%	50%	-9%
TOL	100%	-14%	75%	-14%
WBC	44%	-14.5%	50%	-12%
KYC	31%	-29%	100%	-14%
WMC	42%	-16%	0%	0%
Average of All Stocks	**57%**	**-17%**	**61%**	**-18%**
Median of All Stocks	**48%**	**-14%**	**63%**	**-13%**

Table 3: Sell Signal Confluence and Price Levels

Price Level	**Average Price Retracement (Sell Setups)**	**Average Price Retracement (Sell Countdowns)**
$2.5	-15%	-10%
$3.13	-17%	-15%
$4	-19%	-15%
$5	-16%	-10%
$6.25	-16%	-22%
$9	-11%	-11%
$10	-15%	-20%
$12.5	-12%	-30%
$25	-10%	-8%

Table 4: Confluence in Australian Stock Prices
(Dependent variable = price at swing highs and low)

Psychological Price Barriers	**Coefficient (t-statistics)**	**Sellset Confluence Signals**	**Coefficient (t-statistics)**	**Countdown Confluence Signals**	**Coefficient (t-statistics)**
$1.00	-0.30 (-1.98)**	Sellset*$1.00	-1.06 (-5.78)***	BuyCnt*$1.56	0.83 (7.81)***
$1.56	-0.27 (-2.58)**	Sellset*$1.56	-1.02 (-5.80)***	BuyCnt*$2.00	0.25 (1.93)*
$2.50	-0.14 (-3.06)***	Sellset*$2.00	-0.92 (-3.58)***	BuyCnt*$2.50	0.45 (4.45)***
$4.00	-0.16 (-2.85)***	Sellset*$2.50	-0.97 (-6.70)***	BuyCnt*$3.00	0.19 (2.59)***
$5.00	-0.11 (-1.74)*	Sellset*$3.00	-1.10 (-8.82)***	BuyCnt*$6.00	-1.17 (-24.99)***
$9.00	0.14 (2.34)**	Sellset*$3.13	-0.36 (-1.77)*	BuyCnt*$7.00	0.12 (4.30)***
Price Exhaustion Signals		Sellset*$4.00	-0.45 (-2.75)***	BuyCnt*$9.00	-0.23 (-2.37)**
Buy Setups	-0.50 (-6.22)***	Sellset*$5.00	-0.75 (-5.66)***	BuyCnt*$10.00	-0.41 (-8.89)***
Sell Setups	0.71 (6.46)***	Sellset*$6.00	-0.85 (-6.01)***	BuyCnt*$11.00	-0.36 (-4.19)***
Sell Countdowns	0.32 (2.06)**	Sellset*$7.00	-0.39 (-2.60)***	SellCnt*$2.00	-0.51 (-3.25)***
BuySet Confluence Signals		Sellset*$9.00	-0.36 (-2.30)**		
Buyset*$1.00	1.00 (4.91)***	Sellset*$11.00	-0.29 (-1.66)*		
Buyset*$1.56	0.76 (3.38)***	Sellset*$13.00	0.49 (2.55)**	Constant	-0.63 (-16.50)***
Buyset*$2.00	0.80 (7.71)***	Sellset*$14.00	-0.53 (-3.31)***	Lagged Dependent Variable	0.98 (147.35)***
Buyset*$2.50	0.96 (9.75)***	$\Sigma\beta_i = 0$	2.29***	Highlow	1.51 (48.57)***
Buyset*$3.00	0.67 (5.20)***	$\Sigma\gamma_k = 0$	11.65***	Adjusted R-square	0.97
Buyset*$4.00	0.69 (6.04)***	$\Sigma\delta_m = 0$	22.32***	Sample size	3,840

Equation included individual stock dummies. *,**,*** statistically significant at the 10%, 5% and 1% levels, respectively. Buyset=buy setup, sellset=sell setup, buycnt=buy countdown and sellcnt=sell countdown.

Table 5: Confluence and Price Retracements
(Dependent variable = absolute percentage change of stock price swing)

Variable	**Coefficient (t-statistics)**	**Setup Confluence Signals**	**Coefficient (t-statistics)**	**Countdown Confluence Signals**	**Coefficient (t-statistics)**
Constant	13.99 (27.37)***	Buyset* $1.56	27.94 (2.18)**	Buycnt* $1.56	36.61 (87.97)***
Lagged Dependent variable	0.20 (5.79)***	Buyset* $2.50	-8.75 (-8.74)***	Buycnt* $3.00	-8.54 (-12.32)***
Highlow	-4.57 (-9.99)***	Buyset* $4.00	-5.25 (-3.37)***	Buycnt* $6.00	-6.48 (-8.56)***
Adjusted R-square	0.07	Sellset* $2.00	-5.85 (-2.10)**	Buycnt* $7.00	0.89 (2.19)**
Sample size	3,840	Sellset* $3.13	-5.84 (-4.87)***	Buycnt* $10.00	-2.52 (-6.08)***
Psychological Price Barriers		Sellset* $4.00	-2.28 (-1.98)**	Buycnt* $11.00	-3.07 (-6.35)***
$9.00	-1.83 (-3.23)***	Sellset* $9.00	3.48 (2.64)***	Sellcnt* $2.00	-3.83 (-2.95)***
Price Exhaustion		Sellset* $13.00	-2.17 (-2.86)***		
Sell Setups	-1.83 (-3.98)***				

Equation included individual stock dummies. *,**,*** statistically significant at the 10%, 5% and 1% levels, respectively. Buyset=buy setup, sellset=sell setup, buycnt=buy countdown and sellcnt=sell countdown.

Figure 1: A 9 Day Sell Setup

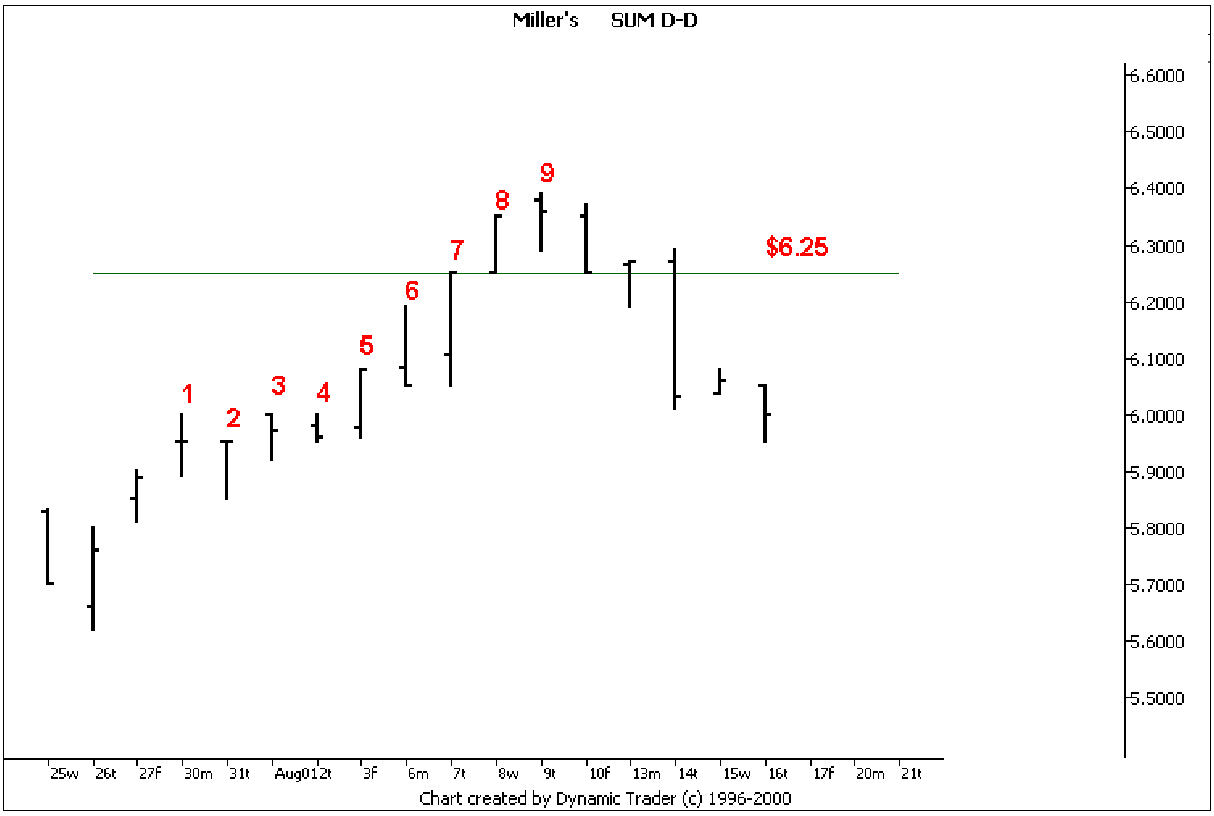

Figure 2: A Sell Countdown

Figure 3: Price and Time Confluence