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Psychological Barriers in Gold Prices?

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Abstract

This paper examines the existence of psychological barriers in a variety of gold price series. Cash, futures and intraday data are examined. Using the now standard M-values of the various series we find some evidence to support the existence of psychological barriers. There is also some evidence that these barriers have an important effect on the conditional mean and variance of the series.

I. Introduction & Motivation

This paper examines the issue of whether or not there are detectable barriers at psychologically important levels (psychological barriers) in a set of gold prices. Signiifcant numbers of commentators attribute particular levles of the gold bullion proce as being ‘barriers’ or ‘support levels’ or in some other manner asb being intrinsicaly more ‘important’ than others. While this phenomenon is not attrobutable to gold alone, with equity indices also being seen as having degrees of psychological barriers inbuilt, gold’s unique position as an asset perhaps provides more scope for this psychological element than others.

< discussion of psychology aspects of gold trading in brief including gold bugs and some examples of quotes from papers> .

This paper is structured therefore as follows. The remainder of this section outlines why numerical psychological barriers may exist in asset prices, and in particular gold. The second section outlines the concept of m-values, pairs of digits that are used to examine the existence of such barriers. The third section outlines the data used, while the fourth section outlines the results from a variety of tests, including uniformity tests, regression barrier tests and tests of conditional returns and volatility conditioned on barriers.

Mitchell (2001) draws a crucial distinction between psychological barriers and clustering phenomena. He provides a significant number of quotations from investment and popular literature in relation to the perceived importance of numbers such as the 10,000 barrier in the Dow, the $400 value in gold etc. He distinguishes clustering, where particular digits etc appear more often from psychological barriers, where trades are infrequent or reluctant at or around a particular cluster of prices. Thus the two elements are related, but not synonymous. Clustering is a necessary, but not a sufficient condition, for a psychological barrier to be present.

One line of analysis has examined the distribution of the sets of digits. This is appealing, as our naieve expectation is that there should be an equal probability of finding a pair of digits such as 87 as that of 92 or 23 or indeed 00, in the absence of barriers. However, the assumption of uniformity runs counter to the implications of Benford's Law. In essence, Benford's law points out that as the various digits, 1,2,3 etc are not increasing at a constant percentage, the limit distribution of such digits need not be uniform. The larger the sample the closer the distribution would be to uniform. Countervailing this the small sample sizes found in many applications implies that the return generating process, typically in assets involving significant autocorrelations, will have a major impact on the distributions. This point, and the implication that tests of uniformity are useful if the data are confined within relatively small ranges, as gold is, are discussed in Ley and Varian (1994) and De Ceuster, Dhaene and Schatteman (1998). Despite the findings of Ley and Varian (1994) and De Ceuster, Dhaene et al. (1998) much work has concentrated on the evaluation of the uniformity of the trailing digits. For example, Koedijk and Stork (1994) use a chi-squared test to reject uniformity in a number of equity indices[1]. Donaldson and Kim (1993) analyses uniformity in a different manner, using instead a regression approach. The regression is of the frequency of the DJIA's trailing digits as the dependent variable against a dummy variable, the dummy taking 1 when it is close[2] to the presupposed psychological barrier of 00. Under the null of no barriers the assumption is that each set of digits, each of the 100 pairs of digits, will be equally likely. Thus, the intercept term is expected to be .01 and the slope coefficient insignificantly different from 0. In this paper and in Donaldson (1990a, b) a variety of equity markets (not, however the Nikkei or the Wiltshire indices) are shown to deviate from this assumption, with negative coefficients on the intercept indicating fewer than hypothesized occurrences of the 00 pair. Burke (2001) uses chi-squared analyses on US government bond indices, again finding that there is significant evidence for deviation from uniformity. A third approach followed in the literature uses regression analysis to assess the impact of being in the neighborhood of a barrier. Koedijk and Stork (1994) study failed to find evidence supporting the significance of 00 barriers in predicting returns. However, this finding has been critiqued by Cyree, Domian, Louton and Yobaccio (1999) for not disaggregating the effects of upward and downward movement. Cyree, Domian et al. (1999) suggest that volatility effects tend to accompany mean effects, and this study finds such

[1] They are able to reject for S&P 500, the Brussels Stock Exchange, the FAZ General, and the FTSE-100, but not for the Nikkei
[2] a variety of measures of closeness are used : within 25 of 00, within 5 etc. The results are qualitatively similar.

differential results. A different approach again to this problem is given by Burke (2001), who hypothesises that the mean effect depends on whether the series is above, below or in the barrier zone while variance effects are dependent merely on being in or out of the barrier area. Using this approach for US bonds he finds no barrier effects in a GARCH framework.

II. M-Values

A number of different approaches have been advocated to examine the potential existence of psychological barriers. These break into three elements: tests of the distribution of the digits, tests of the behaviour of returns around barriers and tests of the frequency of digits around presupposed barriers. Underlying these is the examination of the significant digits of the returns series. Take the two price levels 329.97 and 399.97. If there are no barriers then the probability of any set of trailing digits will be equal to that of any other - the distribution of these will be uniform. It is popularly supposed that barriers exist in gold prices at levels such as 300, 400. If this is the case then we should expect to see relatively fewer 00 digit pairs than pairs such as 01 or 98. Thus for barriers at this level we examine the pair of digits preceding the decimal point. We refer to these as the 10's Digits. For an examination of barriers at levels such as 209.87 or 301.92 we are interested in whether the pair of digits bracketing the decimal point displays a frequency that is different to others. If there exist barriers at levels such as these then we would expect to see relatively fewer xx0.0x digits than otherwise.[3] Thus for a series 309.82 , 301.09 and 298.87 we would extract 09, 01, 98 and 98, 10, 88 as the 10's and 1's digits respectively.

III. Data

A variety of datasets are examined here. As no published work on such barriers in the gold market exists it is important to examine a wide variety of returns. 4 sets of data are examined: daily gold prices from the official London AM fix over the period 2/1/1980 – 31/12/2000, yielding 5478 datapoints; daily data from

[3] More formally, the 10's digits are given as $[P_t] \bmod 100$ and the 1's as $\lfloor 1000 * (P_t^{(\log_{10} P_t) \bmod 1}) \rfloor \bmod 100$, where mod refers to the reduction modulo.. These are known formally as *M*-values. An extensive discussion is provided in De Ceuster, Dhaene et al. (1998)

COMEX for cash and futures gold for the period 2/1/1982 – 28/11/2002, yielding 5255 datapoints ; a high frequency dataset supplied by UBS London, consisting of 15minute interval data over the period 28/8/2001 – 9/1/2003 yielding 12938 datapoints[4]. So far as we are aware no studies of psychological barriers have examined intraday data. All data are expressed in $/Troy Oz. Summary statistics on the series are presented in Table 1 where it is evident that the data are significantly non normal. In order to examine the issues of uniformity and barriers we also calculate the M-values discussed above and derive the frequency of occurrence of each value[5] As all data are less than 1000 in absolute value only tests of the 10's and 1's digits are carried out. Thus we are assessing the existence of barriers around 00 and 0, such as 300 or 330, for example. An interesting feature of the data is that for the high frequency gold the series leaps from 294 to 317 approx, on September 11 2001, reflecting the impact of the terrorist attacks in new york. However, as the series leaps directly between these two elemetns there is no 10's digits around supporsed barrier of 300. Thus, we are unable to test this barrier at this dataseries.

IV. Results

a. Uniformity Tests

A variety of tests have been proposed in relation to the existence of barriers or otherwise. Table 2 provides a test of uniformity of the distribution of the frequency of appearance of the 10's and 1's digits derived from the data. The frequencies themselves are shown in graphical form in The data clearly are not drawn from a uniform distribution. As Ley and Varian (1994) have shown however such a rejection of uniformity is not in itself sufficient to demonstrate the existence of barriers. In addition, De Ceuster, Dhaene et al. (1998) caution that in series that grow without limit, as the series grows and thus the intervals between the barriers widen, the theoretical distribution of digits and frequencies of occurrence is no longer uniform. While the data here are bounded within reasonably tight limits the general applicability of the uniformity argument is

[4] The data are from UBS's proprietary trading system for their own precious metal customers which operates continually. Thus we have a full series of data 24h per day.
[5] These tables are available on request.

weakened by this finding. Accordingly we examine the frequency of the M-values at and near the pre-supposed barriers, as well as the overall shape of the distribution.

b. Barrier Tests

Following Burke (2001), we examine tests designed to measure whether or not yield observations on or near the barriers occur significantly less frequently than a uniform distribution would predict .In general, both tests examine the shape of the frequency distribution for the various decimal digit combinations. The .first focuses on the frequency of observations in close proximity to the barriers: the second examines the entire shape of the frequency distribution . These are referred to as *barrier proximity* and *barrier hump* tests respectively.

We implement the barrier proximity test using Eq. (1) below. The dummy variable takes the value of 1 at the supposed barrier and 0 elsewhere. The test for barriers then resolves to a test of significance of the coefficient on the dummy variable. Under the null of no barriers b will be zero, whereas the presence of barriers will result in a lower frequency of M-values at the barrier and thus b will be negative and significant. Following Donaldson and Kim (1993) and Burke (2001) a number of specifications of the barrier are examined. The first is a strict barrier at the 0 frequency, the second and third are wider tests where the dummy takes the value 1 in the range 90-02 and 95-05 respectively.

$$f(M) = a + bD + e \qquad (1.)$$

The *barrier hump* test on the other hand is implemented with Eq. (2) below, where the frequency of occurrence of each M value is regressed on the M value itself and its square.

$$f(M) = a + fM + gM^2 + h \qquad (2.)$$

The null of no barriers should result in g being zero, while under barriers it will be expected to be negative and significant. Results for these the *barrier proximity* test are show in Table 3, from which it is clear that we can reject the no barriers hypothesis for the 10's digits in all series, but not for the 1's digits. Barriers in the gold price series appear from this test to exist at levels such as 300, 200 etc but not at levels such as 310, 350 etc. Table 4 show the results of the barrier hump test. There is little evidence here of a persistent barrier however.

c. Conditional prediction tests

Shown in are details of conditional prediction tests. We are interested in whether there is any gain in prediction above a simpler specification from barriers. Psychological barriers are generally taken as offering 'support' or 'resistance' to series. Thus it should be possible to gain predicative power from incorporation of such barriers into a model. Unlike Burke (2001) we do not impose assumptions regarding the impact of being in the barrier region. Thus the system estimated for each return series is as below, with the dummy variables D being an indicator of whether the series is in the barrier region or otherwise. Given the similarity of the results for each of the three specifications of barriers we show results for only the 98-02 barrier.

$$\begin{aligned} R_t &= a + bR_{t-1} + fD_{t-1} + e_t \\ e_t &= n_t\sqrt{h_t} \\ h_h &= j + qh_{h-1} + lD_{t-2} + ke_{t-1}^2 \end{aligned} \qquad (3.a\text{-}c)$$

It is clear from the above that this is a GARCH (1,1) estimation, with AR(1,0) specification for the mean equation, all the return series being adequately characterised by this model specification[6]. Interpretation of the model involves an analysis then of the f and l coefficients. Under the null of no predictive value we should see these coefficients being zero. Results are shown in Table 5[7] from which we can see that in all cases there appears to be predictive power for the conditional mean return but not, except for the futures gold, for conditional variance. The signs being negative indicate that in general when the series is in the barrier region that the barrier acts to reduce the next day return. We can therefore interpret this as evidence that these barriers are resistance levels, the series finding it difficult to break through them, as opposed to being a launching pad.

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[6] Results available on request

[7] Although not shown, diagnostic tests indicate that the GARCH models are good fits, with near-normality of residuals, no remaining serial correlation and no remaining ARCH effects

Conclusion

There is a significant literature on psychological barriers, support and resistance levels and the importance of particular numbers in equity and other markets, particularly foreign exchange markets. Despite the psychological elements of the gold market there is much less academic work on these phenomena in the gold market. This note has utilised standard techniques and finds limited evidence that psychological barriers at the 10’s digits (levels such as 200, 300 etc) do prevail in daily gold prices. For high frequency gold the evidence is weaker, but this is perhaps a function of the time period under investigation. The evidence is also indicative of these levels as being resistance rather than support barriers.

Table 1: Summary Statistics

		RETURN SERIES				LEVELS SERIES	
	N	Mean	Std. Deviation	Skewness	Kurtosis	Minimum	Maximum
Gold AM Fix	5478	-0.000119	0.013088	0.183789	19.042788	252.90	843.00
Cash Gold	5255	-0.000041	0.010035	0.071078	13.606823	252.80	509.20
Futures Gold	5255	-0.000048	0.010275	0.223939	9.122686	253.00	510.10
High Frequency Gold	12938	0.000020	0.001571	63.10	5,833.27	270.95	357.10

Table 2: K-S Z Test for Uniformity

	10's Digits		1's digits	
	Z-Stat	p-value	Z-Stat	p-value
Gold AM Fix	4.72	0.00	2.16	0.00
Cash Gold	4.77	0.00	2.12	0.00
Futures gold	4.38	0.00	3.20	0.00
High Frequency Gold	4.75	0.00	5.23	0.00

Table 3: Barrier Proximity Test

		10'S DIGITS			1'S DIGITS		
		b	p-value	R^2	*b*	p-value	R^2
Strict Barrier	Gold AM Fix	-21.000	0.000	0.865	29.505	0.000	0.885
	Cash Gold	-18.740	0.000	0.853	15.596	0.000	0.901
	Futures gold	-8.640	0.000	0.865	1.455	0.030	0.982
	High Frequency gold				255.162	0.000	0.599
9802 Barrier	Gold AM Fix	-15.779	0.000	0.867	-6.937	0.470	0.883
	Cash Gold	-14.063	0.000	0.855	-11.326	0.119	0.902
	Futures gold	-15.326	0.000	0.868	-2.274	0.303	0.983
	High Frequency gold				137.063	0.006	0.606
9505 barrier	Gold AM Fix	-13.960	0.000	0.869	-2.624	0.654	0.883
	Cash Gold	-16.564	0.000	0.861	-5.328	0.264	0.900
	Futures gold	-12.988	0.000	0.870	0.019	0.908	0.983
	High Frequency gold				51.860	0.132	0.586

Table 4 : Barrier Hump Test

	10’S DIGITS			1’S DIGITS		
	g	p-value	R2	*g*	p-value	R2
Gold AM Fix	0.003	0.306	0.912	-0.003	0.249	0.884
Cash Gold	0.002	0.463	0.914	-0.003	0.212	0.901
Futures gold	0.003	0.261	0.926	-0.002	0.027	0.989
High Frequency gold			0.431	0.046	0.002	0.624

Table 5: Conditional Prediction Tests

		a	*b*	*f*	*j*	*q*	*k*	*l*
Gold AM Fix	Coefficient	-0.00021	-0.11040	-0.00198	0.00000	0.92680	0.07570	0.00000
	p-value	*0.04000*	*0.00000*	*0.00790*	*0.00000*	*0.00000*	*0.00000*	*0.31000*
Cash Gold	Coefficient	-0.00014	-0.02500	-0.00148	0.00000	0.95910	0.04280	-0.00000
	p-value	*0.19230*	*0.07560*	*0.00900*	*0.00000*	*0.00000*	*0.00000*	*0.40300*
Future Gold	Coefficient	-0.00013	-0.04920	-0.00098	0.00000	0.92400	0.07270	0.00000
	p-value	*0.21000*	*0.08930*	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00000*

Figure 1

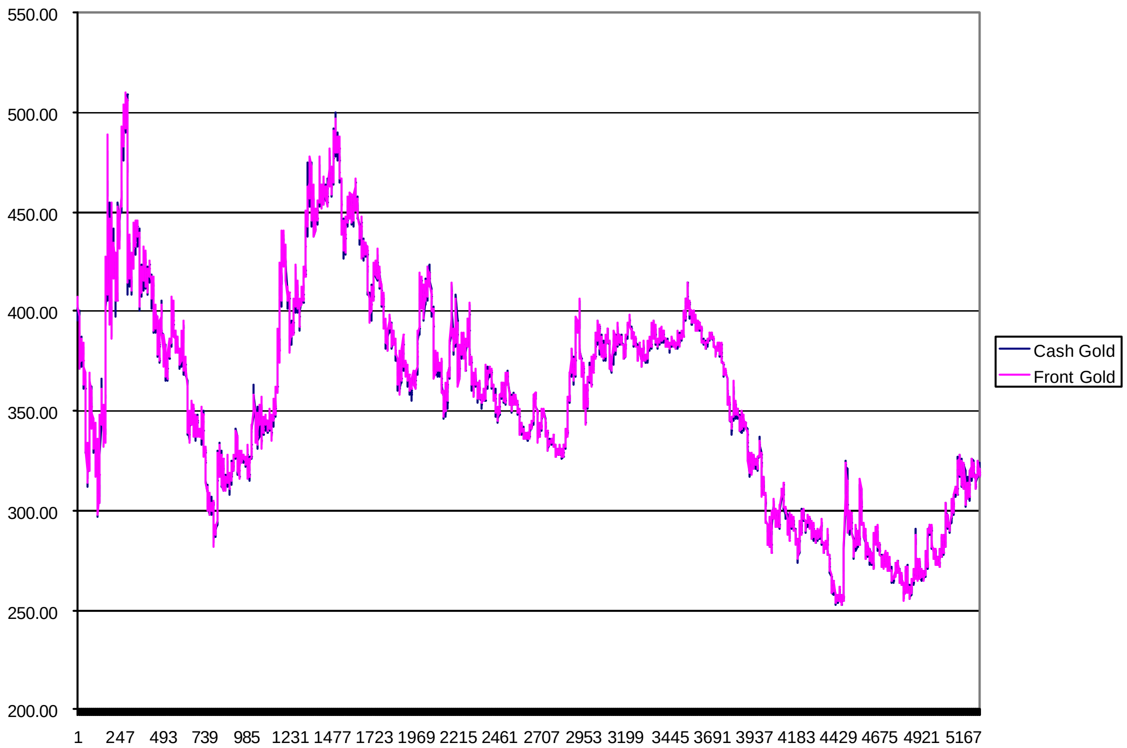
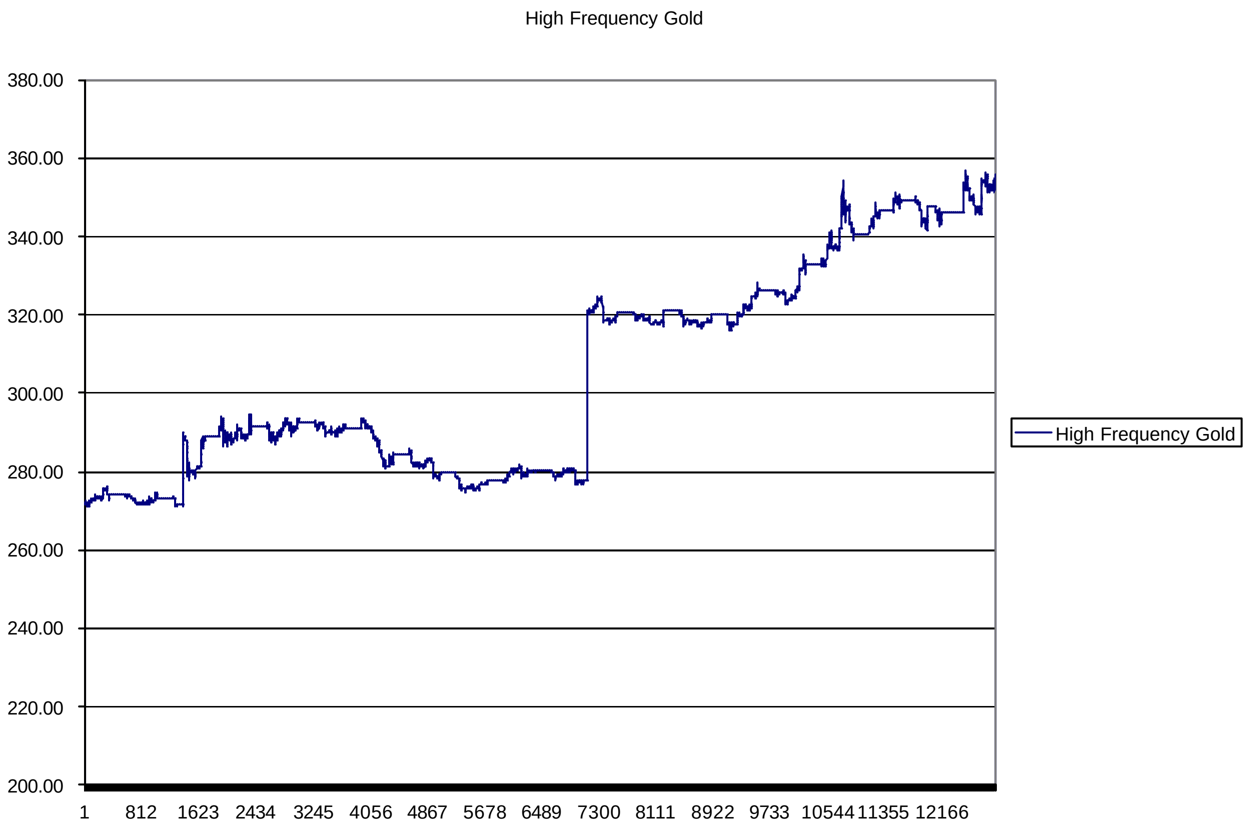


Figure 2

Figure 3



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